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Improving Accuracy and Statistical Reliability of Shoreline Position and Change Rate Estimates

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ABSTRACT

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A generalized methodology, relevant for a wide variety of shoreline change analyses, is developed to estimate the horizontal offset between proxy-based high water line (HWL) type shorelines and datum-based mean high water (MHW) type shorelines. The ability to compute this term is critical for change analyses that incorporate variously defined and derived shoreline estimates because this horizontal offset nearly always acts in one direction; HWL shorelines are landward of MHW shorelines. Not accounting for this offset will cause shoreline change rates to be biased toward slower shoreline retreat, progradation rather than retreat, or faster progradation than in reality (for the typical case where datum-based shorelines are collected after proxy-based shorelines), depending on actual changes at a given site. It is also demonstrated that by computing the uncertainty associated with this proxy datum shoreline bias, we are quantifying, for the first time, the uncertainty of HWL shorelines due to water level fluctuations. Complete accounting of the uncertainty of shoreline position estimates is necessary for determining the statistical significance of shoreline change rate computations. The proxy-datum bias and the bias uncertainty are estimated to be approximately 18 and 9 m, respectively, on average for the sandy beaches of the California coast (and significantly larger on the milder sloping beaches of the U.S. Pacific Northwest). The importance of accounting for the bias in calculating shoreline change rates is confirmed as its inclusion along the California coast changes the coastwide decadal-scale (1970s to present) shoreline change rate from net progradation to net shoreline retreat.

ADDITIONAL INDEX WORDS: *California, Pacific Northwest, high water line, lidar, mean high water, shoreline change rate, shoreline position uncertainty, weighted linear regression*

INTRODUCTION

Intense residential and commercial development is often located just landward of the ever-evolving interface between land and water even though this zone is frequently subjected to a range of natural hazards including flooding, storm impacts, and chronic coastal erosion. Accurately quantifying the rate of change of this interface, *i.e.,* the shoreline change rate, is therefore critical for protecting existing infrastructure and for mitigating damage from expected future changes. Fortunately, in many locations high quality shoreline position estimates date back in excess of 100 years and a variety of methods exist, the most popular being simple linear regression, to compute shoreline change rates and their associated uncertainties (see Genz *et al.,* 2007 for a detailed review of shoreline change rate methods). A benefit of applying ordinary least squares is that because the method assumes that the uncertainty, or variance, of each shoreline estimate is the same, a detailed accounting of all sources of uncertainty is not explicitly necessary. We show, however, that as the methodologies and interpretation of shoreline position extraction have evolved considerably over the last century, care must now be taken to properly quantify and account for all biases and uncertainties in each shoreline position estimate used in change rate computations to ensure the required accuracy necessary for today's coastal management and engineering applications.

Traditionally, the most commonly used proxy for shoreline position, and subsequent change analysis has been the high water line (HWL) (Anders and Byrnes, 1991; Boak and Turner, 2005; Crowell, Leatherman, and Buckley, 1991; Dolan *et al.,* 1980; Leatherman, 1983; Moore, 2000; Morton, 1991; Stafford, 1971). The HWL, often identifiable in aerial photographs and in the field, is typically assumed to represent the landward extent of water during the last high tide and is recognized as a tonal contrast between the wet intertidal beach and the dry supratidal beach (Dolan and Hayden, 1983; Moore, Ruggiero, and List, 2006; Morton, 1979; Pajak and Leatherman, 2002; Zhang *et al.,* 2002). This feature has been considered especially useful in shoreline change studies because the HWL was the preferred boundary for separating land and sea on NOS T-sheets (Shalowitz, 1964). However, since the advent of readily accessible global positioning system (GPS) and light detection and ranging (lidar) data in the 1990s (Leatherman, Douglas, and Labrecque, 2003; List and

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Farris, 1999; Robertson *et al.,* 2004; Ruggiero *et al.,* 2005; Stockdon *et al.,* 2002) datum-based shorelines, typically the horizontal position of MHW or some other vertical datum, have become the modern standard for shoreline position estimates. The MHW tidal datum is defined as the average elevation of all high waters recorded at a particular point or station over a considerable period, usually 19 years (the National Tidal Datum Epoch). A typical approach is to convert the MHW vertical datum to a land-based datum (*i.e.,,* NAVD88) and then locate the horizontal location of the datum using survey data.

It is well known that visually identified HWL-type proxy shorelines are virtually never coincident with datum-based MHW-type shorelines. In fact, HWL shorelines are almost universally estimated to be higher (landward) on the beach profile than MHW shorelines (Moore, Ruggiero, and List, 2006; Morton, Miller, and Moore, 2004; Ruggiero, Kaminsky, and Gelfenbaum, 2003). Morton, Miller, and Moorez (2004) compiled published and unpublished data to evaluate the horizontal and vertical differences in HWL shorelines determined from aerial photographs or field surveys, and the MHW shorelines derived from beach profiles or lidar surveys (Table 1). The HWL and MHW positions were established at the same time, or within a few days of one another at morphodynamically diverse U.S. sites. Because of the short intervals between the derivation of HWL and MHW shorelines, we assume that the reported proxy-datum offsets are primarily artifacts of shoreline definition and are not related to actual changes in the beach profile due to sediment transport. Table 1 reveals that the horizontal magnitude of these offsets can be as high as several tens of meters and that the MHW shoreline is virtually always seaward of the HWL. To our knowledge the only published data where the HWL was seaward of the MHW shoreline for a significant portion of the studied shoreline (three out of eight sites and therefore still a minority) is the work of Robertson *et al.* (2004) in North and South Carolina. Robertson *et al.* (2004) suggest that horizontal and vertical errors in lidar data may be responsible for these results.

Ruggiero, Kaminsky, and Gelfenbaum (2003) and Moore, Ruggiero, and List (2006) hypothesized that the offset between the two shoreline classes, hereafter referred to as the proxy-datum bias or simply the bias, is due to wave driven water level variations on beaches including wave setup and swash oscillations (runup) and therefore is predictable. Comparison of HWL shorelines and a MHW datum-based shoreline for a single-day survey on Assateague Island (Moore, Ruggiero, and List, 2006) revealed an average horizontal offset between shoreline indicators of 18.8 m over a 40-km stretch of coast (Table 1). Vertical offsets were also substantial and were strongly correlated with foreshore beach slope. A simple total water level model that combines the effects of tidal variations and wave runup (Ruggiero *et al.,* 1996, 2001; Ruggiero, Kaminsky, and Gelfenbaum, 2003) successfully reproduced these vertical offsets, confirming that the proxy-datum bias is primarily governed by tide level and wave runup (setup plus swash).

Because the difference between HWL- and MHW-type shorelines is a bias, acting virtually always in the same direction, attempts to correct for the bias in shoreline change analyses result in apparent shoreline change rate shifts. Moore, Ruggiero, and List (2006) concluded that under some circumstances, the resulting rate shift will be a small source of error relative to uncorrected shoreline change rates and will likely not be a major concern. However, they cautioned that given the convergence of several factors, including a gently sloping beach, a moderately short measurement interval, and relatively small change rates, rate shifts due to the bias could begin to represent a substantial percentage of error in shoreline change rates. Under these circumstances, and in particular where rates will be averaged alongshore (common practice in regional shoreline change assessments), determining the bias between shoreline position estimates allows for the quantification of the shoreline change rate shift and the minimization of the associated error.

The accuracy of our ability to estimate shoreline positions has also evolved along with the methodologies used to extract shorelines. Estimates of the uncertainty of HWL shoreline positions are typically a combination of source accuracy (*e.g.,* georeferencing), interpretation error (*e.g.,* T-sheet field mapping techniques), and natural short-term variability consisting of both short-term beach changes and variations in water level prior to data collection. While recent reviews demonstrate the various methodologies for computing some of these sources of uncertainty (*e.g.,* Crowell, Leatherman, and Buckley, 1991; Moore, 2000), the short-term morphological and hydrodynamic variability has historically proven to be the most difficult to quantify. Only site specific, high frequency, and high quality data regarding short term morphodynamic variability, *e.g.,* beach profiling campaigns, are useful for estimating the uncertainty in HWL positions due to sediment transport and associated morphological change (*e.g.,* Ruggiero, Kaminsky, and Gelfenbaum, 2003; Ruggiero *et al.,* 2005; Smith and Zarillo, 1990). Because this type of data is time consuming and expensive to collect, this component of the total uncertainty term is typically ignored and care is taken to use only HWL shorelines from the same season to reduce the magnitude of the uncertainty. Several researchers have documented short-term fluctuations in HWL position due to water level variability to either argue against the use of the HWL as a shoreline proxy (Morton and Speed, 1998; Ruggiero, Kaminsky, and Gelfenbaum, 2003) or to optimize the location of the HWL through the choosing of appropriate seasonal windows when water level variability is particularly low (Pajak and Leatherman, 2002; Zhang *et al.,* 2002). However, until the present study no general approach for estimating this important component of shoreline position uncertainty has been developed.

Unlike HWL shoreline position estimates, the horizontal position of MHW varies only with sediment transport gradients and associated morphological changes (neglecting slow moving changes associated with relative sea level rise). Therefore, datum-based shorelines provide a more repeatable alternative to visual shoreline proxies, eliminating not only the effect of varying hydrodynamic conditions but also variations in shoreline interpretation. Stockdon *et al.* (2002) demonstrate a technique for extracting MHW-datum shoreline estimates from lidar beach profiles with uncertainties approx-

Table 1. *Absolute horizontal and vertical differences between high water line (HWL) and mean high water (MHW) shorelines (modified from Morton et al., 2004).*

Location	HWL Survey Date	MHW Shoreline Survey Date	Length of Shore (km)	Number of Observations	Average Horizontal Offset (m)	Average Vertical Offset (m)	% MHW with Seaward Offset	Data Source or Reference
Galveston Island, TX[1]	01-27-95	01-27-95	Point	1	18	0.6	100	Morton and Speed, 1998
North Padre Island, TX[1]	08-16-95	08-16-95	1.6	6	8	0.4	100	Morton and Speed, 1998
	09-14-95	09-14-95	1.6	6	8	0.2	100	
	09-28-95	09-28-95	1.6	6	12	0.2	100	
	10-06-95	10-06-95	1.6	6	6	0.3	100	
Duck, NC[2]	1994–1996[2]		Point	111	40	2.0	100	Pajak and Leatherman, 2002
Klipsan, WA[3]	05-26-99	05-28-99	3.0	171	22	0.5	100	Ruggiero, Kaminsky, and Gelfenbaum, 2003
	09-21-99	09-24-99	3.0	171	52	0.8	100	
Ocean Shores, WA[3]	05-26-99	05-28-99	4.0	200	23	1.0	100	Ruggiero, Kaminsky, and Gelfenbaum, 2003
	07-27-99	07-22-99	4.0	200	8	0.2	100	
	05-06-01	05-07-01	4.0	200	30	1.0	100	
Oysterville, WA[3]	09-21-99	09-10-99	3.5	201	49	0.9	100	Ruggiero, Kaminsky, and Gelfenbaum, 2003
Assateague Is., MD/VA[1,4]	03-16-98 & 03-17-98	04-03-98	58.6	1172	11	0.7	99	National Park Service (M. Duffy)
	09-29-99 & 10-28-99	10-01-99	60.0	1200	20	1.6	100	
	06-13-01 & 06-14-01	06-05-01	52.4	1049	8	0.6	92	
	10-01-02	09-12-02	47.7	953	22	1.4	98	Coastal Research and Engineering, Inc. (M. Byrnes)
	05-06-02	05-06-02	47	470	18.8	1.2 – 1.3	100	Moore, Ruggiero, and List, 2006

[1] Simultaneous measurement of HWL and MHW at beach profiles coordinated with tide gauge measurements.
[2] Video camera projections of HWL for 111 days during a 3-year period and MHW from generalized beach profiles.
[3] Nearly simultaneous aerial photographs (HWL) and GPS surveys (MHW).
[4] Nearly simultaneous GPS (HWL) and lidar surveys (MHW).

imately an order of magnitude less than typical HWL shoreline estimates. Because the uncertainties in position estimates are significantly different between HWL and MHW shoreline estimates, ordinary least squares analysis is no longer appropriate in shoreline change studies that employ both classes of shorelines. Weighted linear regression is a simple improvement that takes into account time varying uncertainties in shoreline position estimates (Genz *et al.,* 2007). However, as suggested previously, this necessitates a detailed accounting of the uncertainty budgets of each shoreline estimate used in the change analysis.

Because modern regional shoreline position estimates are increasingly derived from lidar data (Hapke *et al.,* 2006; Leatherman, Douglas, and Labrecque, 2003; Robertson *et al.,* 2004; Sallenger *et al.* 2003; Stockdon *et al.,* 2002; Zhang *et al.,* 2002), quantifying the proxy-datum bias is crucial for incorporating modern datum-based shorelines into change analyses that also utilize historical HWL shorelines. In this paper we present a general methodology for estimating the proxy datum bias on a regional scale. The approach can be applied anywhere the foreshore beach slope (typically derived from lidar data) and incident wave climatology can be quantified. We also quantify the uncertainty of our ability to estimate the bias, which is hypothesized to be caused by hydrodynamic processes, and demonstrate that this uncertainty represents the uncertainty term in the total HWL shoreline position error due to water level variations. The impact of the proxy datum bias and the bias uncertainty on shoreline change rate estimates is demonstrated using recently published California shoreline change rates (Hapke *et al.,* 2006; Hapke, Reid, and Richmond, 2009).

METHODOLOGY

Ruggiero, Kaminsky, and Gelfenbaum (2003) and Moore, Ruggiero, and List (2006) developed a technique for estimating the proxy datum bias based on estimates of the total water level (TWL) on beaches

$$\mathrm{TWL} = Z_T + R_{\mathrm{stat}}, \tag{1}$$

which is a combination of tidal level, Z_T, and a statistical representation of the wave runup elevation, R_{stat} (Ruggiero *et al.,* 1996, 2001). This approach of modeling the TWL is similar to that used by the nearshore ARGUS community to estimate shoreline positions (used ultimately to map the intertidal beach) derived from oblique time averaged video images (Aarninkhof *et al.,* 2003; Plant and Holman, 1997; Plant *et al.,* 2007). Here we use an extreme runup statistic, $R_{2\%}$, the 2% exceedence value, to model the total water level because we assume that it is the extreme swash events in a wave runup distribution that are responsible for leaving the markings on a beach visually interpreted to be the HWL. This assumption has been validated by a series of field experiments as reported in Ruggiero, Kaminsky, and Gelfenbaum (2003) and Moore, Ruggiero, and List (2006). In this study we slightly modify the original approach by taking advantage of an updated empirical relation for extreme wave runup elevations (Stockdon *et al.,* 2006) that resulted from analyses of 10 dynamically diverse field experiments. Estimates of the TWL using the Stockdon *et al.* (2006) relation are applicable to natural beaches over a wide range of conditions and can be taken as

$$\mathrm{TWL} = Z_T + 1.1\left\{0.35 \tan\beta (H_0 L_0)^{1/2} + \frac{[H_0 L_0 (0.563 \tan\beta^2 + 0.004)]^{1/2}}{2}\right\}, \tag{2}$$

where $\tan\beta$ is the foreshore beach slope, H_0 is the offshore wave height, L_0 is the offshore wave length, given by linear theory as $(g/2\pi)T^2$, where g is the acceleration of gravity and T is the wave period. By assuming that the foreshore beach slope is approximately linear in the vicinity of MHW, the horizontal offset between the cross-shore position of HWL and MHW shorelines ($X_{\mathrm{HWL}} - X_{\mathrm{MHW}}$), *i.e.,* the proxy datum bias, can be estimated by

$$\begin{aligned}\mathrm{Bias} &= (X_{\mathrm{HWL}} - X_{\mathrm{MHW}}) \\ &= \left(\left[Z_T + 1.1\left\{0.35 \tan\beta (H_0 L_0)^{1/2} + \frac{[H_0 L_0 (0.563 \tan\beta^2 + 0.004)]^{1/2}}{2}\right\}\right] - Z_{\mathrm{MHW}}\right) \Big/ (\tan\beta)\end{aligned} \tag{3}$$

where Z_{MHW} is the mean high water tidal datum. It is evident from Equation (3) that the bias is a function of the tide level, offshore wave conditions, and beach morphology in the form of the foreshore beach slope. In Ruggiero, Kaminsky, and Gelfenbaum (2003) and Moore, Ruggiero, and List (2006), the input to Equation (3) was the local tide, wave, and morphological conditions measured at a particular site at the time of a field experiment. In this paper we turn our attention toward developing a general methodology for computing a best estimate of the bias and the bias uncertainty, relevant for shoreline change studies at long time (decades to centuries) and space (regional shoreline change analyses) scales.

Detailed measurements of wave and beach characteristics are not commonly available for historical HWL estimates and are not typically measured with sufficient alongshore resolution for modern shoreline estimates. Therefore, to calculate a bias useful for regional and long-term shoreline change analysis, we need to derive *long-term* best estimates for beach slope, wave height, wave period (wavelength), and tide level. These best estimates will then be combined in the manner of Equation (3) to give a long-term best estimate of the bias between HWL and MHW shorelines. This best estimate of the bias will also have an estimated uncertainty because each of the variables used to calculate the bias will have an associated uncertainty. If we assume that the uncertainties in our best estimates of beach slope, $\delta_{\tan\beta}$, wave characteristics, δ_{H_0} and δ_{L_0}, and tidal level, δ_{Z_T},

$$\delta_{\mathrm{Bias}} = \left[\left(\frac{\partial \mathrm{Bias}}{\partial \tan\beta}\delta_{\tan\beta}\right)^2 + \left(\frac{\partial \mathrm{Bias}}{\partial H_0}\delta_{H_0}\right)^2 + \left(\frac{\partial \mathrm{Bias}}{\partial L_0}\delta_{L_0}\right)^2 + \left(\frac{\partial \mathrm{Bias}}{\partial Z_T}\delta_{Z_T}\right)^2\right]^{1/2}, \quad (4)$$

where δ_{Bias} is the uncertainty on our computed best guess bias estimate (Taylor, 1997). The four partial derivative terms in Equation (4) are

$$\frac{\partial \mathrm{Bias}}{\partial Z_T} = \frac{1}{\tan\beta} \quad (5)$$

$$\frac{\partial \mathrm{Bias}}{\partial \tan\beta} = \frac{0.31}{[H_0L_0(0.56\tan^2\beta + 0.004)]^{1/2}H_0L_0} + \{[-Z_T - 0.55[H_0L_0(0.56\tan^2\beta + 0.004)]^{1/2} - Z_{\mathrm{MHW}}]/(\tan^2\beta)\} \quad (6)$$

$$\frac{\partial \mathrm{Bias}}{\partial H_0} = \left[\frac{0.19\tan\beta}{(H_0L_0)^{1/2}}L_0 + \frac{0.28}{H_0L_0(0.56\tan^2\beta + 0.004)}\right]^{1/2} \times \frac{L_0(56\tan^2\beta + 0.004)}{\tan\beta} \quad (7)$$

$$\frac{\partial \mathrm{Bias}}{\partial L_0} = \left[\frac{0.19\tan\beta}{(H_0L_0)^{1/2}}H_s + \frac{0.28}{H_0L_0(0.56\tan^2\beta + 0.004)}\right]^{1/2} \times \frac{H_0(56\tan^2\beta + 0.004)}{\tan\beta} \quad (8)$$

and simply require our best estimates of beach slope, wave height, and wavelength to compute.

Best Guess and Uncertainty of Model Input Parameters

In the following sections we discuss the methodology developed for estimating both the "best estimate" and the associated uncertainty of each variable in Equation (3): beach slope, wave height, wavelength, and water level. Because none of these variables is necessarily normally distributed in nature, we do not use standard best guess and uncertainty estimates such as the mean and standard deviation. In the next section, we illustrate our approach for developing a bias uncertainty estimate meant to approximately represent a 90% confidence interval on the best guess bias estimate.

Beach Slope

Wave runup and the magnitude of the bias are sensitive to the foreshore beach slope in the vicinity of MHW. Ideally, multiple measurements of the beach slope at a particular alongshore location would be averaged through time for the best estimate to be applicable to historical HWL shorelines, some developed from data over a century old. However, in most situations, historical beach slopes are not available. Therefore, for our best estimate of beach slope, we take advantage of the high spatial resolution of beach slopes computed using modern lidar data and perform spatial averaging in lieu of the more appropriate, but typically not possible, temporal averaging. As more lidar surveys are completed, temporal averaging will be possible and our methodology will be updated.

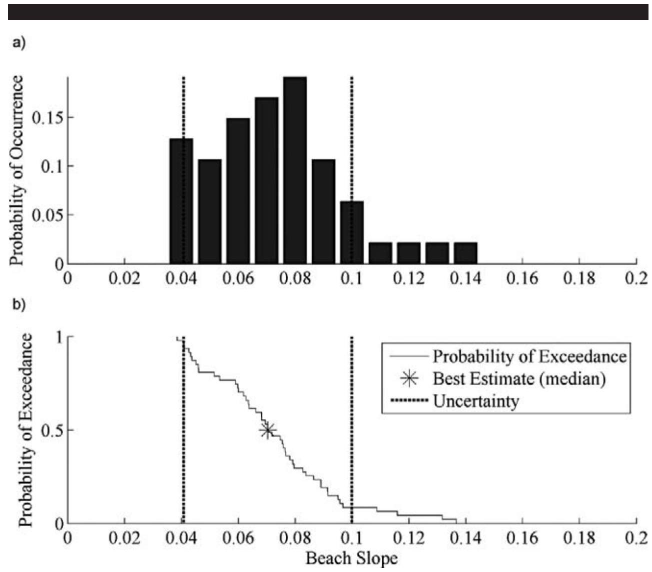

Figure 1. (a) Example 1-km block (northern California) foreshore beach slope probability distribution; (b) foreshore beach slope probability of exceedence with slope best estimate and associated confidence interval.

At present, many open coast sandy shorelines have been flown with lidar (including virtually all of the continental United States, Sallenger *et al.,* 2003). The methodology described in Stockdon *et al.* (2002) is applied here to extract beach slopes at 20-m alongshore intervals because this is typically the spacing used to extract datum-based shorelines from lidar data (Hapke *et al.,* 2006; Morton, Miller, and Moore, 2004). We then take the median of the individual beach slope estimates over 1-km alongshore blocks to develop a best estimate of beach slope to use in calculating the bias. Our choice of estimating the bias at 1-km intervals reflects a trade-off between preserving sufficient alongshore resolution of the bias and removing transitory alongshore variations in slope related to evolving morphological features such as cusps, rip current embayments, mega-cusps, sand waves, *etc.*

Probability distribution functions of a sample of natural beach slopes are bounded on both sides (Figure 1), *i.e.,* it is physically impossible for a beach slope to be less than zero and maximum beach slopes are limited by the grain size and the angle of repose. Because of the bounded nature of natural beach slope distributions, a measure of slope uncertainty such as twice the standard deviation (a 95% confidence limit if the slope distribution could be assumed to be Gaussian) might encompass zero slope or negative slopes, especially where the slope is particularly low to begin with. We therefore need to employ a slope uncertainty statistic that involves the probability of exceedence for the measured beach slope distribution (Figure 1). Here we calculate the 95% exceedance statistic, $\tan\beta\_95\%$, of the foreshore beach slope probability distribution over each 1-km block. The slope uncertainty statistic, $\delta_{\tan\beta}$, is then defined as $\tan\beta\_50\%$ (median beach slope) $\pm \tan\beta\_95\%$, which we use here to approximate a 90% con-

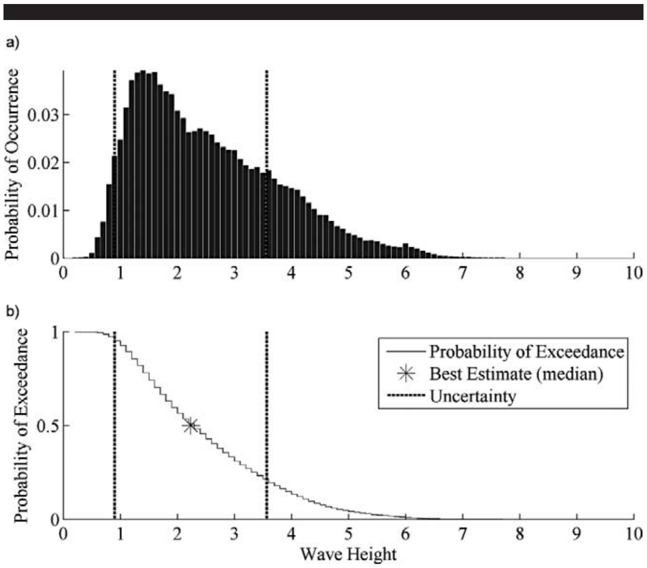

Figure 2. (a) Wave height probability distribution and (b) wave height probability of exceedence with wave height best estimate and associated confidence interval for WIS station P3005.

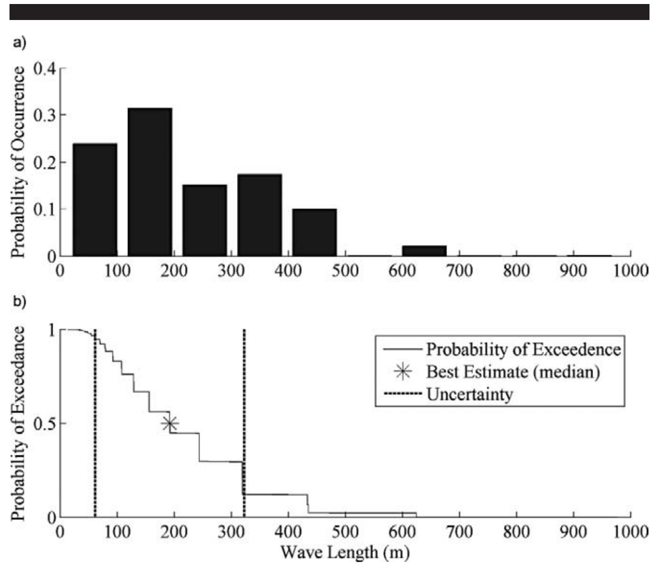

Figure 3. (a) Wavelength probability distribution and (b) wavelength probability of exceedence with wavelength best estimate and associated confidence interval for NDBC buoy 46011 (computed from the wave period using linear wave theory).

fidence interval on the "best estimate" of the beach slope within each 1-km block. We choose to compute our uncertainty estimate using the left-hand side of the probability of exceedence curve in Figure 1, *i.e.,* the 50% exceedance value minus the 95% exceedance value rather than the 5% exceedance value minus the 50% exceedance value, to prevent our confidence interval from extending to zero or a negative slope. Figure 1 illustrates the approach for a single 1-km block of beach slope estimates taken from the northern California coast.

Wave Height and Wavelength

To estimate the bias, we also need a best estimate for the wave height and wavelength (calculated from the peak wave period using linear theory) at the same 1-km blocks over which we calculate the beach slope. Here we take the long-term median wave height and wavelength to be the best estimate to use in the bias calculation. Because *in situ* buoys that measure wave parameters on a regular basis are inconsistently spaced along the United States coast, we derive our best guess of the wave height using wave information studies (WIS) hindcast data. The WIS project (WIS, 2005) produces an online database of hindcast nearshore wave conditions covering U.S. coasts. The hindcast data provide a valuable source of decades-long wave data needed in coastal engineering design, at dense spatial resolution and at a level of temporal continuity not typically available from measurements. The hindcast wave conditions are produced using the numerical ocean wave generation and propagation model WISWAVE along with wind fields (Hanson *et al.,* 2006; Hubertz, 1992). Time series are available at some locations for a densely spaced series of nearshore points along the U.S. coastline (in water depths of 15–20 m), WISIII, and a less-dense series of points in deep water, WISII. Data include hourly wave parameters such as significant wave height, peak period, mean period, mean wave direction, and wind speed and direction. WIS data can be easily downloaded for use as input into nearshore coastal process models.

The WIS period data (and therefore the wavelength computed from these data) were examined and found to be too coarse in frequency resolution to provide reliable uncertainty statistics from probability of exceedence distributions. Therefore, we use *in situ* wave buoy measurements (in the case of the U.S. West Coast both National Data Buoy Center [NDBC, 2005] measurements and Coastal Data Information Program (CDIP, 2005) measurements) for wave period (wavelength). Our period (wavelength) estimates will typically have much poorer alongshore resolution than the wave height estimates (buoy measurements *vs.* hindcast stations), but we assume that the wave period (wavelength) has much less alongshore variation than wave height. The peak wave period from the buoys is used to calculate deep water wavelength as opposed to the average period because Stockdon *et al.* (2006) used the peak period in developing the empirical runup equations we are using in the bias model [Equation (3)].

Because we are again dealing with distributions that are bounded on the low end by zero, we use the probability of exceedence of both wave heights (from WIS data) and wavelengths (from buoy period data) to compute the best estimate uncertainties (Figures 2 and 3). We define δ_{H_0} as H_0–50% $\pm$ H_0–95% and δ_{L_0} as L_0–50% $\pm$ L_0–95%, which again represents an approximation of a 90% confidence interval around our best estimate of the wave parameters. It is important to note that we calculate the deep water wavelength from the periods using linear theory before we calculate the uncertainty statistic (Figure 3).

The WIS station–buoy location that is closest to the average position of each of the 1-km block median slope estimates

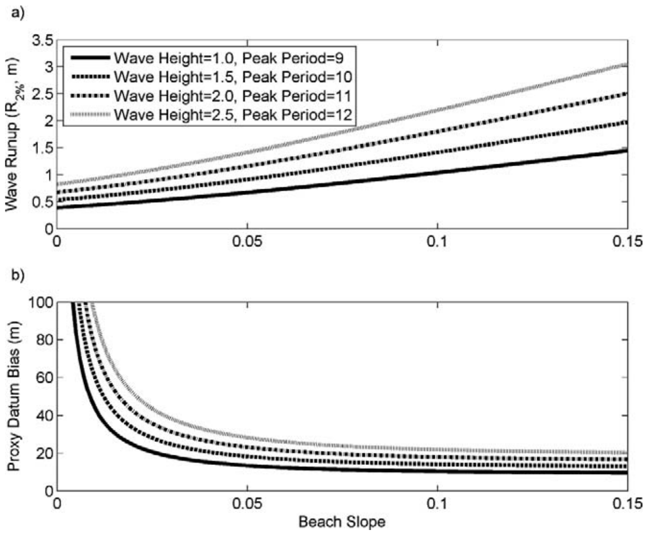

Figure 4. (a) Sensitivity of vertical wave runup to varying beach slopes and wave conditions (varying line types); (b) sensitivity of proxy-datum bias to varying beach slopes and wave conditions (varying line types).

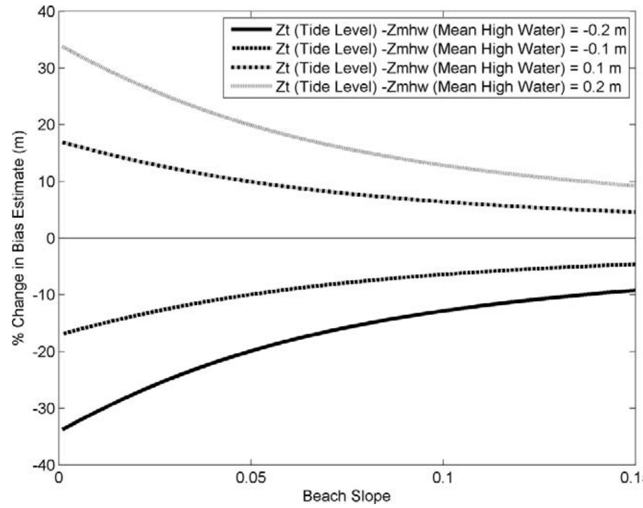

Figure 5. Sensitivity of bias estimate to varying differences between Z_t (tide level) and Z_{MHW} and a range of beach slopes for a representative wave condition ($H_0 = 1.5$ m, $T_p = 11$ s).

is used to estimate the bias. Therefore it is the spacing and alongshore resolution of the beach slope estimates that dictate the spacing and alongshore resolution of the proxy-datum bias and its uncertainty.

Tide Level

We use Z_{MHW} for our best estimate of Z_T in the total water level model, assuming that historical HWL shorelines were formed during high tide water levels that varied randomly around MHW. By assuming that Z_{MHW} is the best estimate for Z_T, we basically eliminate tidal variations at the times of HWL derivation from the problem of estimating the bias. With this assumption, only a best estimate for the horizontal excursion of wave runup (setup plus swash) is necessary to calculate the bias, and therefore Equation (3) simplifies to

$$\begin{aligned}\text{Bias} &= (X_{HWL} - X_{MHW})_{\text{offset}} \\ &= \left[1.1\left\{0.35 \tan\beta (H_0 L_0)^{1/2} + \frac{[H_0 L_0(0.563 \tan\beta^2 + 0.004)]^{1/2}}{2}\right\} \Big/ \tan\beta\right] \quad (9)\end{aligned}$$

The elevation of MHW relative to the land based datum NAVD 88 has been calculated for the continental United States by Weber, List, and Morgan (2005). The uncertainty of assuming that the best estimate water level is Z_{MHW}, δ_{Z_t}, is taken here as the difference between MHHW and MHW, information that is again available in Weber, List, and Morgan (2005).

RESULTS

In the following sections we first investigate the sensitivity of our model for estimating the proxy-datum bias and the bias uncertainty [Equations (3) through (9)] to a variety of input parameter values. We then demonstrate the methodology described previously by giving example computations of best estimates and the associated uncertainty of each variable in Equation (3) for much of the California coast. Data for estimating and applying the bias is derived from a recently published shoreline change assessment of California's sandy coast environment (Hapke *et al.,* 2006; Hapke, Reid, and Richmond, 2009).

Sensitivity of the Bias and Bias Uncertainty

As discussed by Moore, Ruggiero, and List (2006), while a steeper sloping beach has higher vertical wave runup for the same wave conditions as a gently sloping beach, Equation (9) suggests that beach slope and the horizontal proxy-datum offset are inversely proportional. The sensitivity of both extreme wave runup predictions and our estimates of the bias over a range of beach slopes and wave conditions are demonstrated in Figure 4. For beach slopes steeper than approximately 0.05 (1V:20H), variations in wave height and wavelength (period) are most responsible for variability in bias estimates. However, for beach slopes shallower than 0.05, the beach slope itself primarily dictates bias variability. This property of our bias model is most evident in Figure 4b via the asymptotic nature of the bias estimates as beach slopes go toward their lowest limit.

We earlier made the assumption that the best estimate of the water level in our bias estimate is in fact the MHW datum itself. In Figure 5 we illustrate the impact of relaxing this assumption on our bias estimates for a particular set of wave conditions ($H_0 = 1.5$ m, $T_p = 10$ s) and a range of foreshore (planar) beach slopes. We let the difference between the water level, Z_T, and Z_{MHW} vary over 0.4 m, ranging from +0.2 m to −0.2 m. For relatively steep beaches, again slopes steeper than approximately 0.05 (1V:20H), water levels higher or

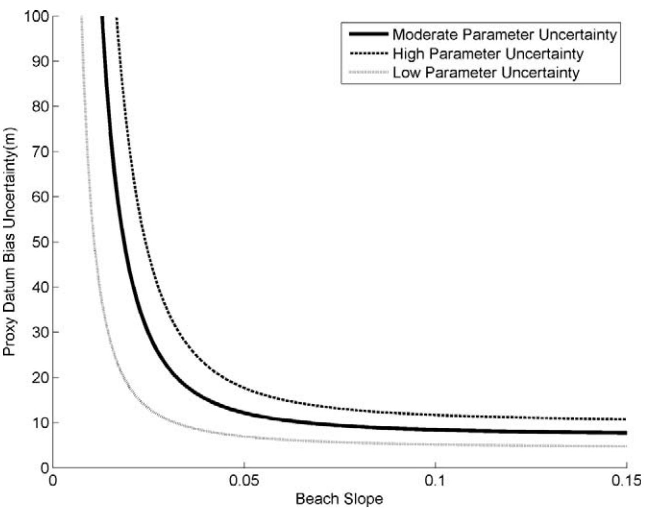

Figure 6. Sensitivity of proxy-datum bias uncertainty estimates to varying beach slopes for a representative wave conditions (H_0 = 1.5 m, T_p = 11 s). The dashed line above the solid curve represents a scenario in which the individual parameters have high uncertainty (Table 2) and the dotted line below the solid curve represents a scenario with low uncertainty (Table 2).

Table 2. *Values used to examine the sensitivity of the bias uncertainty to a range of input variables (Figure 6) including the uncertainty in the best estimates of those variables.*

	Uncertainty Scenario		
Parameter	Low	Moderate	High
$\delta_{\tan\beta}$	0.01	0.03	0.05
δ_{H_0}	0.5 (m)	1.0 (m)	1.5 (m)
δ_{L_0}	100 (m)	150 (m)	200 (m)
δ_{Z_T}	0.05 (m)	0.10 (m)	0.15 (m)

lower than MHW have minimal effect on the bias estimate (less than 20%). Even on relatively shallow sloping beaches, the minor impact, relative to the other parameters, that a varying tide level has on the bias prediction justifies our assumption of using MHW as the best estimate water level.

Examination of Equations (4) through (8) reveals that the bias uncertainty is sensitive not only to the beach slope, wave height, and wavelength but also to the uncertainty of our best estimate of each of these terms. Figure 6 illustrates the sensitivity of the bias uncertainty for a range of foreshore beach slopes and the same wave conditions used in Figure 5. As with the bias itself, the bias uncertainty is relatively insensitive to beach slope above values of approximately 0.05 but very sensitive to flatter beach slopes. The solid line is computed assuming moderate uncertainties in the individual parameters (Table 2) while the dashed and dotted lines above and below the solid line represent high and low uncertainties, respectively, for the representative wave condition. The proxy datum bias uncertainty is relatively insensitive to varying input wave heights and periods over a reasonable range (not shown).

Bias and Bias Uncertainty Estimates along the California Coast

Data from 96 WIS stations (Figure 7) and 18 wave buoys (NDBC and CDIP) have been used to calculate the time averaged alongshore varying median wave height and wave period (wavelength) along the California coast. The alongshore-averaged long-term median wave height for the state, derived from the WIS data, is approximately 1.6 m with values ranging from 0.6 (southern California where the Channel Islands limit wave energy at the shoreline) to 2.5 m (northern California). Figure 7 illustrates the alongshore-varying best estimate wave height as well as our estimates of the uncertainty of the best estimate. In general there is a trend of increasing long-term median wave height with increasing latitude. The median wave heights estimated from the WIS data compare well with similar estimates derived from the buoy data (not shown). We therefore take advantage of the significant increase in alongshore resolution provided by the WIS data. The analysis of buoy data gives an alongshore averaged median wave period (wavelength) of 11.4 seconds (205 m), with a relatively narrow range of 10.0 to 13.8 seconds (156 to 297 m). While the range is narrow, our estimate of the uncertainty of the best estimate wave period (wavelength) is relatively wide because of the coarse frequency resolution of the wave period measurements (Figure 3).

For the state of California we have identified 815 one-kilometer stretches of sandy coast in which there is enough lidar data (flown in 2002) to generate a reasonable estimate of the foreshore beach slope (Figure 8). The alongshore average of the 815 one-kilometer block median beach slopes (Figure 7) is 0.089 (5.1°) ranging from 0.026 (1.5°) to 0.21

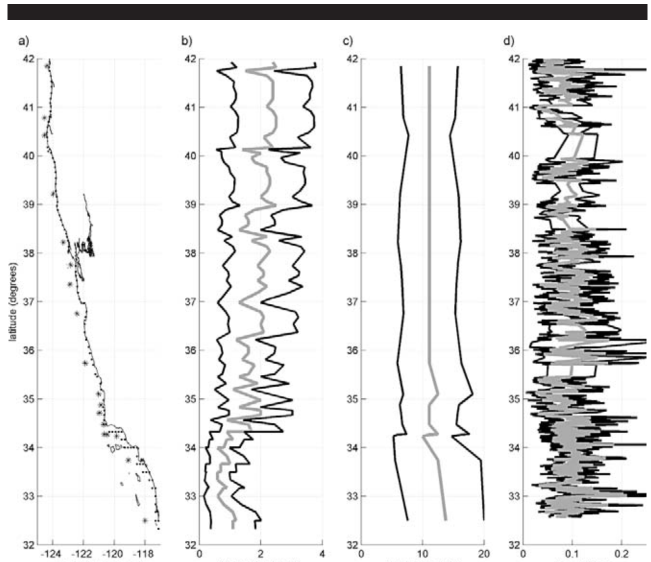

Figure 7. (a) Location of WIS stations, black dots, and buoy data, black asterisks, along the California coast; (b) wave height best estimates and confidence interval for each 1-km block; (c) wave period best estimates and confidence interval for each 1-km block; and (d) beach slope best estimates and confidence interval for each 1-km block.

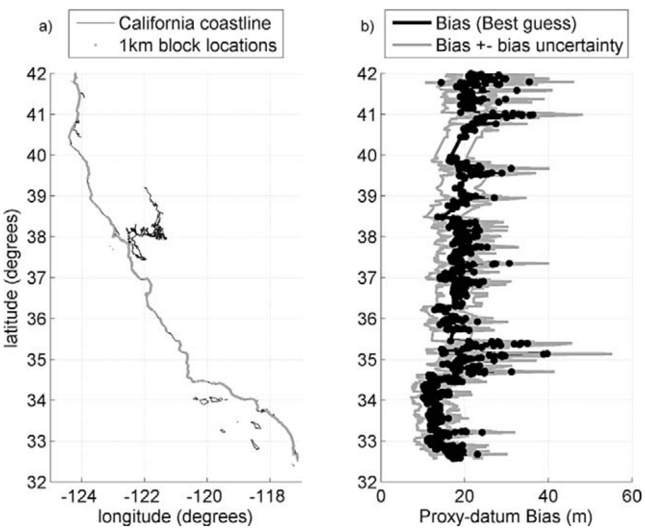

Figure 8. (a) Location of each 1-km block along the California coastline where we estimate the (b) proxy-datum bias and the bias uncertainty.

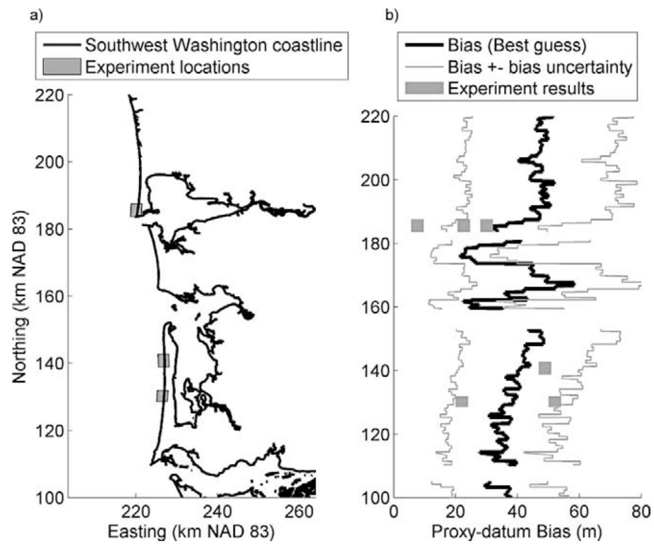

Figure 9. (a) Locations of the proxy-datum bias experiments (polygons) described in Ruggiero, Kaminsky, and Gelfenbaum (2003) along the southwest Washington coast; (b) bias (dark line) and the bias uncertainty (gray lines) for southwest Washington State. The gray bars show the results of the six field experiments.

(11.9°). The sensitivity curves shown in Figures 4 and 6 indicate that for the majority of the California coast we can assume that the temporal variability of 1-km block averaged beach slopes would probably not have a large impact on estimates of the bias and the bias uncertainty because of the flatness of the sensitivity curves in the vicinity of the average beach slopes. Less than 10% of the 1-km blocks have a median beach slope less than 0.05.

Equation (9) and our best estimates of beach slope, wave height, and wavelength (Figure 7) have been used to compute the proxy datum bias for the 815 one-kilometer blocks along the California coastline (Figure 8). The alongshore averaged best estimate of the bias for the state is 17.9 m ranging from 10.1 to 39.7 m. The wave height, wavelength, tidal level, and beach slope data (and their uncertainties) are also combined to calculate the proxy datum bias uncertainty [Equations (4) through (8)]. The uncertainty of each of the 815 bias estimates for the state of California is also reported in Figure 8. The alongshore averaged uncertainty is ±8.7 m ranging from 4.9 to 28.3 m.

DISCUSSION

A preponderance of evidence, including the total water level modeling of Ruggiero, Kaminsky, and Gelfenbaum (2003) and Moore, Ruggiero, and List (2006) and the data gathered from around the country (Table 1, Morton, Miller, and Moore, 2004), suggests that the HWL is virtually always landward of the MHW shoreline. It follows that to make accurate estimates of shoreline change rates, the bias must be estimated and corrected for. Below we first validate our methodology by comparing bias estimates in Washington State with field measurements. We then show that our estimates of the bias uncertainty are in fact also estimates of the uncertainty of HWL shorelines due to water level variations, an important term in the shoreline position error budget. Finally, we discuss the impact of the bias and the bias uncertainty on calculating shoreline change rates.

Model Validation

We have applied the methodology described to estimate the bias and bias uncertainty of the sandy open coast beaches of southwest Washington State in the U.S. Pacific Northwest (PNW). The mean bias along these fine grained, low sloping beaches (Ruggiero *et al.,* 2005) is approximately 40 m with a mean bias uncertainty of approximately 20 m (Figure 9). The bias and the bias uncertainty are larger in the PNW than in California primarily because the beach slopes are typically flatter (wave heights are also larger) and as demonstrated, both parameters are particularly sensitive to mild foreshore beach slopes.

Ruggiero, Kaminsky, and Gelfenbaum (2003) report on six field experiments in which topographic surveys were collected nearly simultaneously with aerial photography along various beaches of southwest Washington (Table 1). The tests clearly showed that the HWL, determined from aerial photography, was higher on the beach and well landward of the horizontal location of MHW because over the approximately 24 km of coastline surveyed during these experiments the mean observed bias was 30.6 m. The observations from the six experiments described in Ruggiero, Kaminsky, and Gelfenbaum (2003) are shown in comparison to our regional estimates in Figure 9. The observed biases in five of the six experiments fall within the computed confidence interval on our estimated bias. In the one experiment in which the observed bias is significantly less than our estimated range for the bias, Ocean Shores, Washington, 22–27 July 1999 (Table 1), the HWL was derived 5 days after the horizontal location

Table 3. *Estimated shoreline position uncertainties for California shorelines (modified from Hapke et al., 2006)*

Shoreline Position Uncertainties (m)	Period 1	2	3	4
Georeferencing (source accuracy)	4	4	4	—
Digitizing (source accuracy)	1	1	1	—
T-sheet shoreline position (interpretation uncertainty)	10	10	3	—
Shoreline position uncertainty due to water level variations	9	9	9	—
Lidar shoreline positioning error	—	—	—	1.5
Total HWL uncertainty without shoreline variability uncertainty	10.8	10.8	5.1	1.5
Total HWL uncertainty with shoreline variability uncertainty	14.1	14.1	10.3	1.5

Periods: 1 = 1800s (T-sheet), 2 = 1920s (T-sheet), 3 = 1970s (photocontrolled T-sheet), 4 = post-1997 (lidar survey)

of MHW was derived. July is typically a month when the beaches of the PNW are prograding relatively rapidly (Ruggiero, Kaminsky, and Gelfenbaum, 2003), and it is conceivable that the observed bias for this experiment underestimates reality.

Quantifying the Uncertainty of HWL-Type Shorelines

Three primary components comprise the total uncertainty in shoreline position estimates: source accuracy, shoreline interpretation error, and short-term shoreline variability. Anders and Byrnes (1991), Crowell, Leatherman, and Buckley (1991), and Moore (2000) provide general estimates of typical measurement errors associated with shoreline source accuracy, *i.e.,* registry of shoreline position relative to geographic coordinates and shoreline digitizing. The largest shoreline position errors are typically on the order of ±10 m and are associated with shoreline interpretation uncertainty in the original surveys used to generate historical T-sheets. Estimates of these sources of error for California shorelines derived from T-sheets and lidar surveys are summarized in Table 3 and follow the work of Hapke *et al.* (2006). As discussed, a previously unaccounted for error term in most shoreline change analyses is the uncertainty in HWL shorelines due to variations in water levels.

Our methodology for computing the bias [Equation (9)] gives us a best estimate of the horizontal location of the water level (landward of MHW) primarily responsible for generating HWL-type shorelines. We assume that any particular historical HWL shoreline was generated by a water level that varied randomly above and below this best estimate location. Therefore, by also calculating the proxy datum bias uncertainty, an approximate 90% confidence interval on our best estimate of the bias, we have developed a general methodology for quantifying the HWL shoreline position uncertainty due to water level fluctuations for the first time.

The HWL shoreline position uncertainty due to water levels for the state of California is on average approximately 9 m (Figure 8). Table 3 demonstrates the impact of including this term on the total HWL shoreline uncertainty budget. For periods 1 (1800s) and 2 (1920s), when the shoreline interpretation uncertainty is already relatively high, including the uncertainty due to water levels increases the total uncertainty from 10.8 to 14.1 m, an increase of approximately 30%. However, for period 3 (1970s), when photocontrolled T-sheets have reduced the interpretation uncertainty significantly, including the uncertainty due to water levels increases the total uncertainty by over 100% (5.1 to 10.3 m). Note that the total uncertainty values, with and without the water level fluctuation term, are computed by adding the individual terms in quadrature (*i.e.,* square root of the sum of the squares, Taylor, 1997) rather than by simple addition.

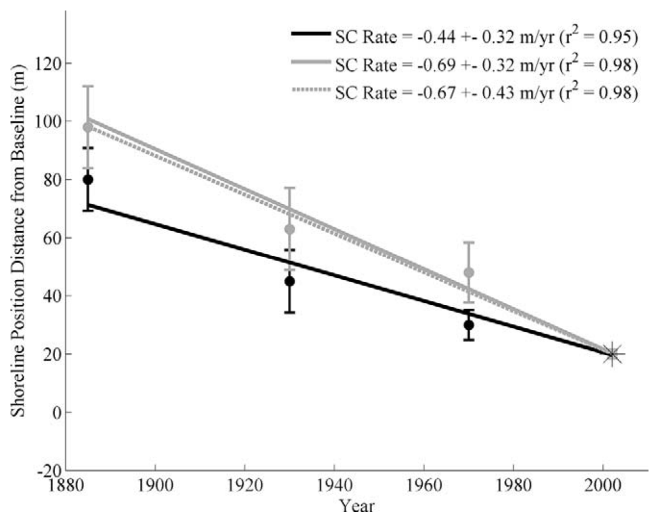

Figure 10. Example shoreline change analysis illustrating the impact of the bias and bias uncertainty on shoreline change rates and rate significance. Black circles and black error bars represent the unadjusted shoreline position with the black solid line being the result of a weighted least squares linear regression. Gray circles and gray error bars represent the bias adjusted shoreline positions with the solid gray line again being the result of weighted linear regression. The dashed gray line includes the influence of both the bias adjustment and the bias uncertainty on the shoreline change rate (and associated error) estimate.

Impact of the Bias and Bias Uncertainty on Shoreline Change Rates

Conceptually the proxy datum bias could be applied to either datum-based shorelines (move them landward up beach) or proxy-based shorelines (move them seaward down beach). In our approach, we apply the bias to historical HWL estimates because we only want to adjust shorelines known to be less accurate and because we foresee that future shorelines will continue to be datum-based. Once the relevant data are collected, it is relatively straightforward to apply the bias correction and to then determine the effect the bias has on estimating shoreline change rates. In Figure 10 we illustrate the impact of the bias and the bias uncertainty on shoreline change rates for a simple synthetic times series of proxy-based and datum-based shorelines. In this example three proxy-based HWL-type shorelines (1885, 1930, and 1970) are followed by a single datum-based MHW-type shoreline (2002). A proxy-datum bias of 18 m (the average value for

California), with an uncertainty of 9 m, is applied to the HWL shorelines only, moving them seaward relative to the baseline (Figure 10).

Simple linear regression is a preferred and frequently cited applied statistical technique for expressing shoreline movement and estimating rates of change (Genz *et al.,* 2007). However, because we know that the uncertainties of the shoreline position estimates in our example vary considerably with time, we apply a weighted least squares linear regression analysis to the raw and bias-adjusted data. In weighted linear regression, more reliable data is given greater emphasis, or weight. In our example, shorelines are weighted as one over the square of the total position uncertainty (Table 3), resulting in a best-fit line that places greater emphasis on data points where the shoreline position uncertainty is lower (*e.g.,* the datum-based shoreline derived from lidar data). We note here that typically in weighted linear regression the uncertainties are expressed as the square root of the variance of the data, *i.e.,* at the 68% confidence interval. Unfortunately, in historical shoreline change analyses, it is usually unknown at what confidence level the various uncertainty terms, *e.g.,* source accuracy, are expressed. Here we assume that these uncertainty values (Table 3) are conservative and therefore similar to our estimated 90% confidence interval on the position uncertainty due to total water level variations.

The raw (unadjusted) shoreline change rate (Figure 10, solid black line), using position uncertainty values without including the bias uncertainty term, is computed to be 0.44 $\pm$ 0.32 m per year of shoreline retreat ($r^2 = 0.95$). After applying the proxy-datum bias to the historical HWL shorelines, but still not including the bias uncertainty in the position uncertainty estimates, the shoreline change rate (solid gray line) is estimated to be 0.69 $\pm$ 0.32 m per year of retreat ($r^2 = 0.98$), a 57% increase in the annual retreat rate. Finally, the shoreline change rate (dashed gray line) is estimated to be 0.67 $\pm$ 0.43 m per year of retreat ($r^2 = 0.98$) when we include the effect of the bias uncertainty on the shoreline position uncertainty estimates. While the inclusion of the bias uncertainty has a relatively minor impact on the slope of the weighted least squares regression line (estimated retreat rate), the uncertainty of the slope estimate increases significantly because of the increase in the uncertainty of the individual shorelines. In the synthetic test presented here, the shoreline change rate remains significantly greater than zero but there is clearly the possibility that the inclusion of the bias uncertainty can change a shoreline change rate from being significantly different than zero to not significantly different than zero.

The impact of the bias and the inclusion of the uncertainty term due to water level fluctuations in shoreline position uncertainty estimates is even more strongly felt when shoreline change rates are computed using the end-point methodology. For the example shown in Figure 10, the unadjusted short-term shoreline change rate (1970–2002) is estimated to be 0.31 $\pm$ 0.17 m per year of retreat. For this decadal-scale analysis, the error bar on the shoreline change rate is calculated as the square root of the sum of the squared individual uncertainty terms divided by the period between the two shorelines. Applying the bias to the 1970 shoreline and the bias uncertainty to the position uncertainty for that shoreline changes the shoreline change rate to 0.88 $\pm$ 0.33 m per year of retreat, a 180% increase in the retreat rate and a doubling of the shoreline change rate uncertainty.

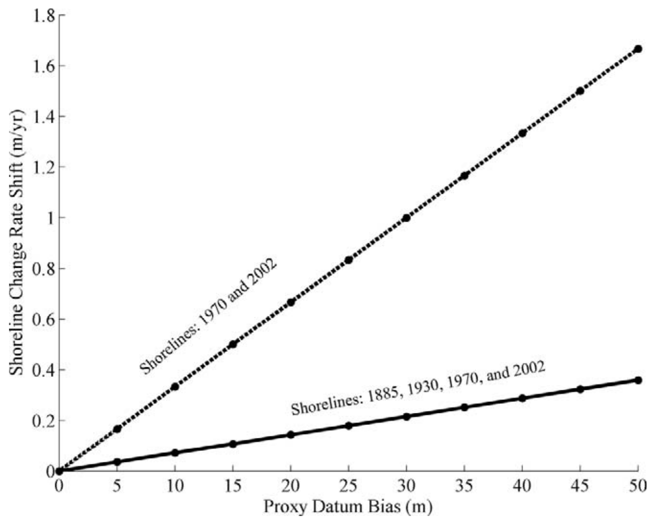

Figure 11. The generalized impact, in terms of a shoreline change rate shift, of the proxy-datum bias on both long-term and short-term shoreline change rates (for the given set of dates).

The impact of the bias on shoreline change rates can be generalized to some extent. Figure 11 demonstrates the variability of the shoreline change rate shift due to the bias for a range of bias values. In this example we demonstrate the rate shift for both a short-term end point shoreline change analysis and for a long-term linear regression type analysis. The curves are generated for the specific dates shown on Figure 11; however, it is relatively simple to recast these curves for any set of dates. A proxy-datum bias of only approximately 30 m (the value computed for southwest Washington State) results in a short-term (decadal-scale) shoreline change rate shift of 1.0 m/y.

Finally, we demonstrate the impact of the bias and bias uncertainty on the shoreline change rates recently reported for all sandy beaches within the state of California in the study of Hapke *et al.* (2006) and Hapke, Reid, and Richmond (2009). The authors of this report split up the state into 15 analysis regions, each roughly 100 km in length, and here we examine the influence of the bias using these same regions. Figure 12 shows unadjusted shoreline change rates, the shoreline change rate shifts, and the adjusted shoreline change rates for both a short-term (decadal-scale) and long-term (century-scale) analysis. As discussed, to estimate the rate shift associated with the bias we need to know the dates used in both the short-term and long-term shoreline change analysis. The shoreline position dates used in the shoreline change analysis varied within the 15 regions, so for this demonstration we have simply averaged the dates used for all shoreline change transects in a particular region.

In the unadjusted analysis, only 1 of the 15 analysis regions was retreating over the long-term while 4 of the 15

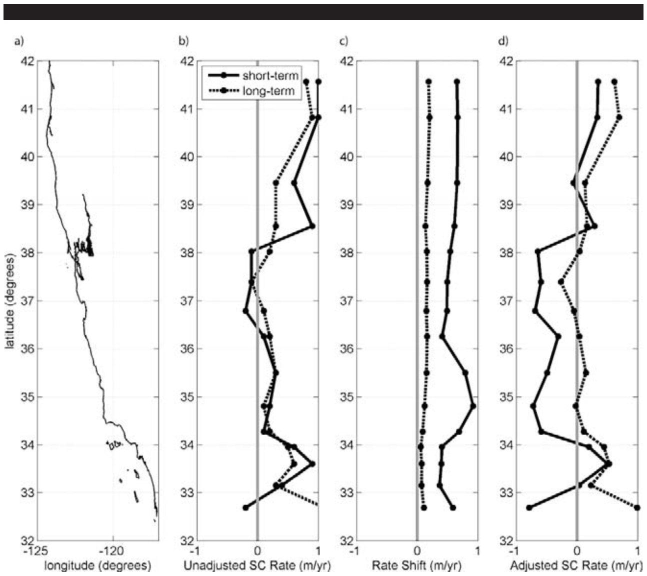

Figure 12. (a) Map of the California coastline; (b) the unadjusted shoreline change rates, long-term and short-term, for the 15 analysis regions within the state; (c) the proxy-datum bias induced shoreline change rate shifts associated with both the long-term and short-term shoreline change analyses, and (d) the adjusted shoreline change rates for the state of California.

were retreating over the short-term (Figure 12). The long-term shoreline change rate shift averaged approximately 0.18 m/y for the entire state while the short-term rate shift averaged 0.58 m/y. Applying the rate shifts due to the proxy-datum bias increases the number of analysis regions with a long-term trend of retreat to three and a short-term trend of retreat to nine. The statewide average long-term shoreline change signal is progradational with and without the bias correction. However, the bias reduces the rate of progradation approximately 30%. For the short-term analysis, the application of the bias to the shoreline change rates resulted in the statewide short-term shoreline change rate changing from one of progradation (0.37 m/y) to one of retreat (0.21 m/y).

CONCLUSIONS

For more than 150 years, the HWL has served as the authoritative shoreline proxy because it could be visually identified in the field. With advanced technologies, such as GPS and lidar, it is now becoming standard practice to define the shoreline on the basis of an elevation contour such as the MHW tidal datum. Changing the shoreline definition from a proxy-based physical feature that is uncontrolled in terms of an elevation datum to a datum-based shoreline defined by an elevation has important implications with regard to inferred changes in shoreline position and calculated rates of change. Accurately quantifying and accounting for the proxy datum bias and the bias uncertainty can be crucial for the proper representation of shoreline change rates. The nearly systematic horizontal offset between the HWL and the MHW shoreline could cause reported shoreline positions and calculated rates of change to be biased toward slower retreat, progradation rather than retreat, or faster progradation than in reality, depending on actual changes at a given site.

This paper has presented a general methodology for estimating the proxy datum bias and the bias uncertainty relevant for long-term and large-scale shoreline change studies. The methodology can be applied anywhere that foreshore beach slopes and offshore incident wave conditions can be quantified. We have demonstrated that applying the bias to short-term shoreline change rates in the state of California has significant implications, *i.e.,* the sign of the shoreline change signal changed from progradation to retreat. It is probable that the bias could have equal importance in other sandy coastal regions and potentially be even more important along dissipative beaches with relatively shallow beach slopes (such as the U.S. Pacific Northwest).

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