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Toward Parsimony in Shoreline Change Prediction (II): Applying Basis Function Methods to Real and Synthetic Data

Ayesha S. Genz, L. Neil Frazer, and Charles H. Fletcher*

Department of Geology and Geophysics
School of Ocean and Earth Science and Technology
University of Hawaii
1680 East West Road
Honolulu, HI 96822, U.S.A.
agenz@hawaii.edu
neil@hawaii.edu
fletcher@soest.hawaii.edu

ABSTRACT

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There is a need to supply coastal managers with statistically defensible hazard predictions that can be used to implement coastal setbacks and other management policies. The goal of this article is to evaluate the widely used single-transect method, as well as several new methods: t-binning, IC-binning, polynomial methods, and eigenbeaches, to identify which method(s) best predicts a 50-year eroded shoreline position. The polynomial and eigenbeach methods allow for acceleration (the rates vary with time). The methods are compared using data from nine beaches on Maui, Hawaii, and four sets of synthetic data. Evaluations of the methods are based on an information criterion, color maps of residuals, long-term (50 year) predictions, and cross-validating the most recent shoreline, which has a short-term span of 5–9 years. The newer methods identified significant rates at 74% of the transects, *vs.* 0% for single-transect on beaches in Maui, Hawaii. The cross-validation results showed that the polynomial and eigenbeach methods, without acceleration, best predicted the most recent shoreline. Contrary to the cross-validation results, synthetic results showed that the polynomial and eigenbeach methods with acceleration predicted the 50-year shoreline better than methods without acceleration. Nonacceleration methods predicted short-term positions better, and acceleration methods predicted long-term positions better. We conclude that the polynomial and eigenbeach methods improve the significance of the rates compared with the single-transect method.

ADDITIONAL INDEX WORDS: *Coastal erosion, shoreline change rates, Hawaii beaches, coastal management, erosion hazard zones, information criterion.*

INTRODUCTION

This article is the second of a two-part series on predicting future shorelines. The first article (hereinafter, article 1) focused on the theoretical framework of methods of shoreline change, introducing three new basis function methods: IC-binning, polynomial methods, and eigenbeaches. Article 1 also examined various information criteria (IC) that can be used to find parameters and compare methods. In this article, we applied the new and existing methods to discover which method best predicted long-term change.

By identifying the most accurate method for predicting future shorelines, coastal managers can apply construction setbacks and other management tools based on statistically defensible, future hazard zone. Currently, 23 of the 29 coastal U.S. states and territories establish construction setbacks (Bernd-Cohen and Gordon, 1999). Of those, 8 states use erosion rates in determining setbacks (Heinz Center, 2000). Erosion rates for all these setbacks are based on the single-transect (ST) method of calculating a rate at each shore-normal transect along a beach, which is problematic because nearby transects are not independent of each other.

For this study, we defined a hazard zone as the 50-year shoreline prediction at the 95% confidence interval. This time frame was based on the Maui County, Hawaii, construction setback laws. The new and existing statistical methods are evaluated by applying them to beaches on Maui, Hawaii. We also used synthetic data to compare long-term predictions for all methods, specifically, the 50-year hazard predictions. MATLAB codes for the methods in this article are available from the authors.

STUDY AREA

Maui, Hawaii, beaches are divided into three regions with distinct wave regimes: Kihei, West Maui, and the North Shore (*e.g.,* Fletcher *et al.,* 2003; Rooney *et al.,* 2003) (Figure 1). Kihei is predominantly affected by south swells, refracted north swells, and kona storm waves. Kona storms are low-pressure systems that generate wind and wave action from the south and southwest. West Maui is affected by North Pa-

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* Corresponding author.

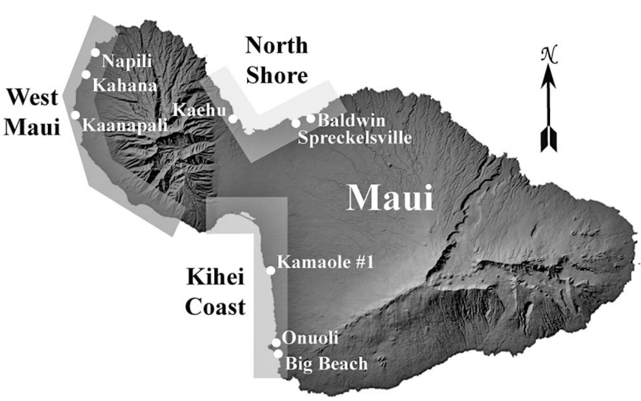

Figure 1. Sandy beaches on Maui, Hawaii, fall into three distinct regions: Kihei, West Maui, and the North Shore.

cific swells, south swells, and kona storm waves, whereas the North Shore is influenced by North Pacific swells and trade wind waves (Eversole and Fletcher, 2003; Fletcher *et al.,* 2002; Makai Ocean Engineering and Sea Engineering, 1991; Rooney and Fletcher, 2005). The beaches in Maui, Hawaii, are predominantly sandy (calcareous) and are either pocket beaches or longer, open-ended beaches. Unlike the East and Gulf coasts of the United States, Maui, Hawaii, does not contain barrier islands; therefore, in this article, we did not test barrier island beaches.

We tested three beaches within each region that included both hardened and natural shorelines (Table 1). At Kihei, we tested Big Beach, Kamaole 1, and Onuoli. All three are sandy beaches, with no hardened structures, and no offshore fringing reefs. The backshore of Kamaole 1 is developed with hotels and private homes (Makai Ocean Engineering and Sea Engineering, 1991).

Baldwin, Kaehu, and Spreckelsville are found at the North Shore of Maui, Hawaii. Baldwin is a large sandy beach with two offshore rock platforms at either end of the beach. The rock platform on the east end of the beach acted as a tombolo, with land accreting in front of the rock platform in the early 1900s. Since then, shoreline recession has decreased the tombolo effect, resulting in massive erosion on the adjacent beach. Similar to Baldwin, Spreckelsville has an offshore protective rock outcrop, which previously acted as a tombolo but is currently eroding at a high rate. A revetment, built after 1975, is directly onshore of this feature (Makai Ocean Engineering and Sea Engineering, 1991). Kaehu is a cobble beach offering some protection from large North Pacific swells. Two stream mouths act as borders at each end of the beach. Kaehu does not contain any hardening structures.

The three beaches from West Maui are Kaanapali, Kahana, and Napili. Kaanapali is a 1.15-km, white, sandy beach, which is affected by strong seasonal changes. Beach profile data in Kaanapali suggest that beach width varies an average of 50 m seasonally (Eversole and Fletcher, 2003; Vitousek *et al.,* 2007). An offshore shallow fringing reef is present at this beach, and the backshore is highly developed with many resorts. Kahana is 0.67 km long and north of Kaanapali, with a developed backshore. Revetments are found on both ends of the beach, making them convenient littoral boundaries. Napili is a small pocket beach north of Kahana. Its backshore is developed with hotels and residences. The offshore for both Kahana and Napili is basaltic rock (Makai Ocean Engineering and Sea Engineering, 1991).

Maui, Hawaii, shoreline positions are produced from two types of images: aerial orthophotographs and National Oceanic and Atmospheric Administration (NOAA) topographic sheets (T-sheets), which pass the National Map Accuracy Standards. Shore-normal transects are spaced at 20 m, and the low-water mark is digitized as the shoreline position (Fletcher *et al.,* 2003). Studies specific to the Hawaiian coast indicate that the low-water mark, as evidenced by a morphologic feature (the beach toe), is an accurate proxy of shoreline change (Coyne, Fletcher, and Richmond 1999; Fletcher *et al.,* 2003; Rooney and Fletcher, 2000). Because our baselines are located offshore, if the low-water mark increases landward over time, the beach is eroding; hence, in change-rate calculations a positive slope indicates erosion and a negative slope indicates accretion. The measurement and position uncertainties used in our generalized least squares (GLS) procedure are the errors associated with the process of generating shoreline positions (see Fletcher *et al.,* 2003, for discussion of errors and uncertainties in this data set).

METHODS

Of the existing shoreline change methods, ST is the most widely used method in calculating shoreline change today (Table 2). Change rates are calculated at each transect using shoreline data in different years from that transect only. Thus, neighboring transects do not influence the rate at a specific transect. A variety of methods have been used to calculate the change rate at each transect (*e.g.,* endpoint rate, average of rates, least squares) (*e.g.,* Crowell, Douglas, and Leatherman, 1997; Dean and Malakar, 1999; Dolan, Fenster, and Holme, 1991; Fenster, Dolan, and Elder, 1993; Honeycutt, Crowell, and Douglas, 2001).

T-Binning (or t-bin) was recently introduced by Genz *et al.* (2007) as an alternative to ST. t-Bin identifies groups of transects that have indistinguishable rates by calculating rates of different transect groups, then comparing the groups using the Student's t-test. If the rates at the groups are not significantly different, then the groups are combined into a larger group with a single rate. User-input is needed to identify the bins. In contrast to ST, t-bin does not assume transects are independent of each other. t-Bin rates, however, are discontinuous in the alongshore direction (spatially, along the beach). The rate of one bin of transects can differ greatly from the rate of an adjacent bin of transects, which is unlikely to be an accurate portrayal of beach processes.

Article 1 introduced IC-binning (or IC-bin), polynomial methods, and eigenbeaches as new techniques for quantifying shoreline change. Here, we apply those new methods, along with ST and t-bin, to shoreline data from nine beaches in Maui, Hawaii. IC-bin is similar to t-bin, except that it doesn't use the Student's t-test and doesn't require user input. IC-bin uses an IC to identify bins. IC-bin starts with a one-bin

Table 1. *A description of the nine beaches that were used to test the different shoreline change methods.*

Region	Wave Climate	Beach	Description	Offshore Bottom	Structures	No. of Shorelines	Shoreline Years
Kihei	South swell, refracted north swell and tradewind waves	Big Beach	>1 km undeveloped sandy beach	No fringing reef; rock and sandy bottom	None	5	1949–1997
		Kamaole 1	~1 km sandy beach; backshore developed with hotels and private homes	No fringing reef; sandy bottom	None	7	1912–1997
		Onuoli	~1 km undeveloped sandy beach	No fringing reef; rock and sandy bottom	None	8	1931–1997
North Shore	North Pacific swell and tradewind waves	Baldwin	>1 km sandy beach with sand dunes in backshore	Two offshore rock benches—one on each end of the beach	Revetment just east of the beach built between 1950 and 1960	5	1912–2002
		Kaehu	>1 km cobble beach	Fringing reef	None; stream mouths border each end of the beach	7	1912–2002
		Spreckelsville	~1 km sandy beach with private homes in the backshore	Offshore protective reef in the center of the beach	Revetments and seawalls in the center and eastern end of the beach	6	1912–2002
West Maui	North Pacific swell, south swell, and kona storm waves	Kaanapali	>1 km sandy beach; highly developed with hotels; landscaped vegetation line	Shallow fringing reef in the southern end of beach	None	9	1912–1997
		Kahana	~1 km sandy beach with hotels and private homes	Shallow reef	Revetments at each end of the beach	6	1912–1997
		Napili	<1 km sandy, pocket beach with hotels and private homes	Shallow reef	None	7	1912–1997

Table 2. *A description of the shoreline change methods.*

	Method	Basis Function	Acceleration?
	Single-transect (ST)	Delta function	no
Binning	t-Binning (T-BIN)	Boxcar	no
	IC-Binning (IC-BIN)	Boxcar	no
Polynomial methods	LX	Legendre polynomials	no
	LXT	Legendre polynomials	yes
	RX	Trigonometric functions	no
	RXT	Trigonometric functions	yes
Eigenbeaches	EX	Principal components of beach data	no
	EXT	Principal components of beach data	yes

model that groups all transects into one bin and calculates an IC score. Next, an IC score is calculated for each possible two-bin models. The two-bin model with the lowest IC score is the best-fit two-bin model. The bin model increases by 1, and the best-fit three-bin model is identified. The bin model (whether it is a one-bin model, a two-bin model, or higher) with the lowest IC score is the IC-bin model. The IC used throughout this article was a form of the Akaike Information Criterion (AIC_u) (McQuarrie and Tsai, 1998).

Polynomial methods include four methods, all of which use basis functions on a finite interval to describe shoreline change (Frazer, Genz, and Fletcher, 2008; article 1). Basis functions are building blocks used to create functions by linear combination. Legendre polynomial method (LX) and Legendre polynomial method with acceleration (LXT) use Legendre polynomials as their basis functions. Legendre polynomials are used with all shorelines, at all transects, to model the rate and/or acceleration along a beach. For LX, the change rate varies spatially alongshore, but not with time. LXT allows for acceleration in the shoreline change rate, which can be positive or negative (deceleration) in the model, letting the change rate vary both temporally and spatially. The acceleration is assumed to be constant through time, but the rate is allowed to vary. Trigonometric function method (RX) and trigonometric function method with acceleration (RXT) are similar to LX and LXT, respectively, except that they use the trigonometric functions sine and cosine as their basis. The reason for using different basis functions is that Legendre polynomials include a linear basis function that does not exist in the trigonometric functions sine and cosine. Thus, for a beach, where rate increases linearly in the alongshore direction, Legendre polynomials give a more parsimonious description of the shoreline data than sines and cosines.

Similar to polynomial methods, eigenbeaches includes two methods—one that permits acceleration (EXT) and one that excludes acceleration (EX) (Frazer, Genz, and Fletcher, 2008; article 1). The basis functions for EX and EXT are the principal components of all the shoreline data at all transects. RXT, LXT, and EXT do not assume that acceleration is present in the data, but they allow acceleration if it improves the fit of the model to data as indicated by the IC scores. When acceleration does not improve the fit, LXT, RXT, and EXT automatically revert to LX, RX, and EX, respectively.

Altogether, we evaluated a total of nine methods, all of which use GLS. An IC score is calculated for each method. As noted above, the IC used throughout this article was AIC_u. For each method, we calculate an AIC_u score for all transects having no rate and an AIC_u score with a rate. The AIC_u score with the lowest value is reported for that method.

Shoreline Data Analysis

Shoreline data from the nine study sites in Maui, Hawaii, range from 1912 to 2002. The number of shorelines at each beach ranges from five shorelines (two beaches) to nine shorelines (one beach). We applied all nine basis function methods to Maui, Hawaii, data and compared them using four different standards. We used the IC score to evaluate all methods. The IC score is used in two ways: first, to find the number of basis functions in each method; and second, to compare all nine methods to each other. The basis function method with the lowest IC score is considered the best method for the beach in question.

We also examined the data residuals of each method along a beach. Residuals are generated by subtracting the modeled shoreline position from the known shoreline position. If a beach has five transects and five shorelines, there are 25 residuals. Each method will produce five modeled shorelines (ST must be repeated five times, once at each transect, whereas all other methods need a synthetic data set once). A method that results in low residuals, models a shoreline better than a method that produces high residuals. For visual interpretation, color maps of the residuals were created. These were used to look for patterns of misfit. In particular, we wanted to know whether the rate discontinuities at bin borders lead to larger residuals near the borders; if so, then binning may not be an appropriate method for that beach. Conversely, if a method with smooth basis functions, such as RX, has residuals that change sign at specific beach locations, a binning method may be superior for that beach.

We also calculated the 50-year predicted hazard position to determine whether different methods predict similar future positions. If different methods agree, the credibility of the 50-year prediction is increased.

Finally, we used the cross-validation approach to predict the most recent shoreline using all methods. To do this, we assigned all shorelines, except the most recent shoreline, to our training data set. The most recent shoreline was the testing datum. We then modeled the training data to predict the testing datum. Although this is a short-term prediction (5–9 years), it allowed us to compare the accuracy for each method using real data. As our data are limited, long-term predictions, such as a 50-year prediction, using real data were not practical. Similar to Honeycutt, Crowell, and Douglas (2001), we calculated the error in prediction (EIP), which is the difference between the predicted and testing datum. The mean EIP indicates whether a method is overestimating or underestimating the shoreline, and the mean of the absolute values of the EIP (or |EIP|) estimates the average magnitude of the error. We compared the mean |EIP| for each method with an analysis of variance (ANOVA) test at the 95% confidence interval.

Synthetic Analysis

Crowell, Douglas, and Leatherman (1997) used sea-level data to compare minimum description length to endpoint rate and least-squares regression. As the sea-level database is historically rich, Crowell, Douglas, and Leatherman (1997) were able to compare short-term and long-term predictions by depleting historical sea-level data to mimic temporal distributions of historical shorelines. They compared forecasts made with such data to a nondepleted, more recent test period. We did a similar long-term comparison, but we used synthetic data in lieu of sea-level data. An advantage of using synthetic data is that one can assign a true value before introducing noise to the data and then compare the resulting predictions to the true value. However, unlike synthetically derived data, the short-term and long-term fluctuations of sea-level data resemble those of shoreline data (Crowell, Douglas, and Leatherman, 1997). Also, the simulated noise in the synthetic data may be a poor model for noise in actual data. In the analysis of synthetic data, we focused on long-term changes because we wanted to identify the basis function method that best predicts future hazard zones.

We generated a synthetic beach that had 25 transects with 11 shorelines ranging in years from 1900 to 2000 (one shoreline *per* decade). We used a beach of 25 transects because it reflected a typical medium-sized Maui, Hawaii, beach. We assigned known terms for rate, intercept, and acceleration to generate the synthetic shorelines and a "future" shoreline position at year 2050. We then generated Gaussian noise for each synthetic shoreline. Before adding the noise to the shoreline positions, we ran a one-quarter, one-half, one-quarter smoother on the noise three times for each time series to correlate the noise in the alongshore direction. Once the noise was added to the shoreline data, we attempted to predict the synthetic 2050 shoreline position using all nine methods.

We ran four different synthetic data sets, varying the rate and acceleration spatially for each synthetic data set to determine which method best describes shoreline change under differing rate-change circumstances. Also, we examined the effects of including acceleration in the analysis of data that have no true acceleration and the effects of excluding acceleration from the analysis of data that actually contain acceleration. Within each synthetic data set, 50 trials of Gaussian noise were used. The noise process had a zero mean with a standard deviation of five times the true rate.

In synthetic data set 1, the parameters did not vary spatially. The intercept, rate, and acceleration were constant in the alongshore direction. We assigned a rate of 1 m/y, an intercept of 3 m, and an acceleration of 0.01 m/y/y at each transect.

In synthetic data set 2, the intercept and acceleration were constant in the alongshore direction. Their values were the same as in synthetic data set 1. The rate, however, varied along the beach (modeled by a polynomial).

In synthetic data set 3, the intercept and rate were constant in the spatial direction and had the same values as synthetic data set 1. The acceleration term varied along the beach (modeled by a polynomial). Although we allowed acceleration to vary spatially, it was constant temporally. Acceleration did not change over time—it changed based on the location of the transect along the beach.

In synthetic data set 4, the intercept was constant along the beach and was equivalent to the value in synthetic data set 1. The rate, which was modeled by a polynomial, varied along the beach. We omitted the acceleration term in this synthetic data set to see how well the methods that allow for acceleration performed.

RESULTS

Shoreline Data Analysis

If acceleration is allowed, then the change rates vary through time at each transect. Therefore, when we discuss rates from acceleration methods, we refer to the rates at each transect at the most recent year. If the IC score identifies no rate, then the change rate is zero.

Overall, Kihei showed acceleration on one beach. Big Beach had no rates for ST, EX, and EXT. LXT and RXT did not find acceleration and, therefore, reverted to LX and RX, respectively. LX and RX modeled a constant erosion rate (0.26 m/y) along the beach. IC-bin identified five bins; however, bin models greater than five bins could have a lower IC score. IC-bin only tested models up to five bins because Big Beach is a large beach and testing models greater than five bins on large beaches was too time intensive (a six-bin model took more than 7 d for a synthetic data set). With the five-bin model, the erosion rate was constant (0.29 m/y) in the northern half of the beach, decreasing to 0.001 m/y in the southern part of the beach. t-Bin identified three bins with similar, but less-dramatic, erosion-rate trends. All methods, except for LXT, RXT, and EXT, identified no rates for Kamaole, *i.e.,* the change rates were equal to zero for this beach. LXT and RXT identified acceleration that was constant in the alongshore direction. EXT found acceleration varying in the alongshore direction, with the rates having minimal to no erosion in the north and accretion to the south. For Onuoli, all methods followed a similar spatial pattern of erosion except ST, which identified no rates within this beach. Erosion rates are higher in the southern part of Onuoli and lower in the northern part of the beach. Acceleration was not identified at this beach.

North Shore showed acceleration for two of the three beaches. For Baldwin, t-bin, IC-bin, LX, RX, and EX showed erosion throughout the beach, with erosion increasing near the offshore rock bench on the western end of Baldwin. EXT did not find acceleration and equaled EX. Acceleration was detected by LXT and RXT, with slow accretion for most of the beach and rapid erosion near the offshore rock bench at the

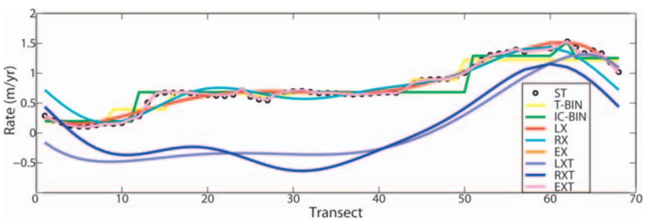

Figure 2. Rates for Baldwin. Rates found with single-transect (open circles) are not significant. t-Bin found eight bins and IC-bin found five bins. LXT and RXT found acceleration at this beach. EXT did not find acceleration and equaled EX.

western end (Figure 2). Single-transect was the only method that had no rates for Kaehu. All methods, except ST showed accretion at the northern end of the beach, followed by low to no erosion for the rest of the beach. LXT and RXT found acceleration and higher erosion rates than the other methods. Similar to Kaehu, ST was the only method that had no rates for Spreckelsville. All methods indicated erosion for Spreckelsville, with much higher erosion rates on the shoreline fronting the offshore reef platform. No acceleration was detected at this beach. LX had the lowest erosion rates for the area fronting the offshore reef platform because it identified a constant erosion rate that did not fluctuate in the alongshore direction.

EXT was the only method that detected acceleration in two of the three beaches in West Maui. Single-transect, t-bin, and IC-bin found no rates for Kaanapali. Only EXT identified acceleration, and its rate trend differed greatly from the other methods. EXT found accretion in the south part of the beach, whereas all other methods with rates found erosion. At the northern part of Kaanapali, LX and RX found accretion, and EX and EXT found erosion. At Kahana, ST found no rates. EXT indicated acceleration, and its rates differed greatly from all other methods. EXT rates showed minimal erosion throughout the beach. The other methods showed high erosion throughout the beach, with the highest erosion found in the central portion of the beach. Single-transect found no rates for Napili and no acceleration. t-Bin, LX, and RX found rates that were constant in the alongshore direction. IC-bin and EX showed higher erosion on the central part of the beach.

IC Scores

In comparing IC scores across methods, acceleration methods had the lowest IC score for four of the nine beaches. Table 3 shows the ΔAIC_u scores, with the lowest score equal to zero. EX equaled EXT (EXT did not find acceleration) at Onuoli and Spreckelsville. LX equaled LXT at Kaanapali. LXT and RXT had the lowest IC for Kamaole. IC-bin had the lowest score for Big Beach and Napili. Single-transect had the highest IC score for seven of the nine beaches. IC-Bin had the highest score for Kamaole and Kaanapali.

Residuals

We analyzed residuals to see whether discrete borders (from binning) affected the residuals in the alongshore direction. Residuals between known shorelines and modeled shorelines ranged between −59.1 m and 50.73 m. This large range is attributed to high residuals in Baldwin. When comparing the magnitude of the mean residuals (or mean |residuals|), EXT had the lowest residuals for five of the nine beaches (Table 4). For all five of these beaches, EXT found acceleration. IC-bin had the lowest residuals for Big Beach (IC-bin also had the lowest IC score at this beach). EX equaled EXT at Spreckelsville and had the lowest residuals. t-Bin, LX, and RX had the lowest residuals at Napili (LXT and RXT did not find acceleration, so it equaled LX and RX, respectively). t-Bin and IC-bin had the highest residuals for two beaches. LX and RX had the highest residuals at Big Beach. LX and RX also had highest residuals at Spreckelsville and Baldwin, respectively. LXT and RXT had the highest residuals at Kamaole.

Although differing methods had lowest mean |residuals| at differing beaches, they were not significantly different from all other methods (excluding binning at two beaches, binning did worse) on seven of the nine beaches. Significance, in this case, refers to the 95% confidence level from an ANOVA test on the |residuals| of all methods. At Baldwin, LXT had the lowest mean |residuals|; LXT and RXT were significantly different from all other methods. AT Kaehu, EXT had the lowest mean |residuals|, but was not significantly different from EX, LX, and LXT.

Of the seven beaches that had bins, only Onuoli, Baldwin, and Spreckelsville had slightly higher residuals at the edge of the borders (Figure 3). The other four beaches showed no discernibly high residuals at the bin borders.

Table 3. *ΔIC scores.*

	Kihei			North Shore			West Maui		
Method	Big	Kamaole 1	Onuoli	Baldwin	Kaehu	Spreckelsville	Kaanapali	Kahana	Napili
ST	1.60	1.80	1.33	2.53	1.02	2.43	1.50	2.17	0.56
t-Bin	0.41	0.03	0.50	0.59	0.47	0.42	0.03	0.38	0.05
IC-bin	0	1.82	0.24	0.21	0.24	0.32	1.51	0.23	0
LX	0.35	0.03	0.31	0.20	0.27	0.34	0	0.19	0.05
RX	0.35	0.03	0.30	0.27	0.49	0.29	0.02	0.23	0.05
EX	0.43	0.03	0	0.11	0.11	0	0.01	0.08	0.04
LXT	0.35	0	0.31	0	0.27	0.34	0	0.19	0.05
RXT	0.35	0	0.30	0.08	0.49	0.29	0.02	0.23	0.05
EXT	0.43	0.03	0	0.11	0	0	0.03	0	0.04

Table 4. *Mean of the absolute value of the residuals (|residuals|) results.*

Method	Mean |residual| (m)								
	Kihei			North Shore			West Maui		
	Big Beach	Kamaole 1	Onuoli	Baldwin	Kaehu	Spreckelsville	Kaanapali	Kahana	Napili
ST	—	—	—	—	—	—	—	—	—
t-Bin	3.80	—	3.49	9.40	3.07	5.86	—	3.44	4.83
IC-bin	3.76	—	3.15	9.32	3.27	5.32	—	3.40	4.89
LX	4.05	—	3.39	9.33	2.89	6.08	9.08	3.36	4.83
RX	4.05	—	3.26	9.58	3.26	5.23	9.09	3.40	4.83
EX	—	—	2.86	9.17	2.91	5.06	9.11	3.42	4.86
LXT	4.05	11.32	3.39	6.31	2.56	6.08	9.08	3.36	4.83
RXT	4.05	11.32	3.26	6.79	3.26	5.23	9.09	3.40	4.83
EXT	—	10.09	2.86	9.17	2.41	5.06	8.98	2.66	4.86
Min (m)	3.76	10.09	2.86	6.31	2.41	5.06	8.98	2.66	4.83
Max (m)	4.05	11.32	3.49	9.58	3.27	6.08	9.11	3.44	4.89
Difference (m)	0.29	1.23	0.63	3.27	0.86	1.02	0.13	0.79	0.06

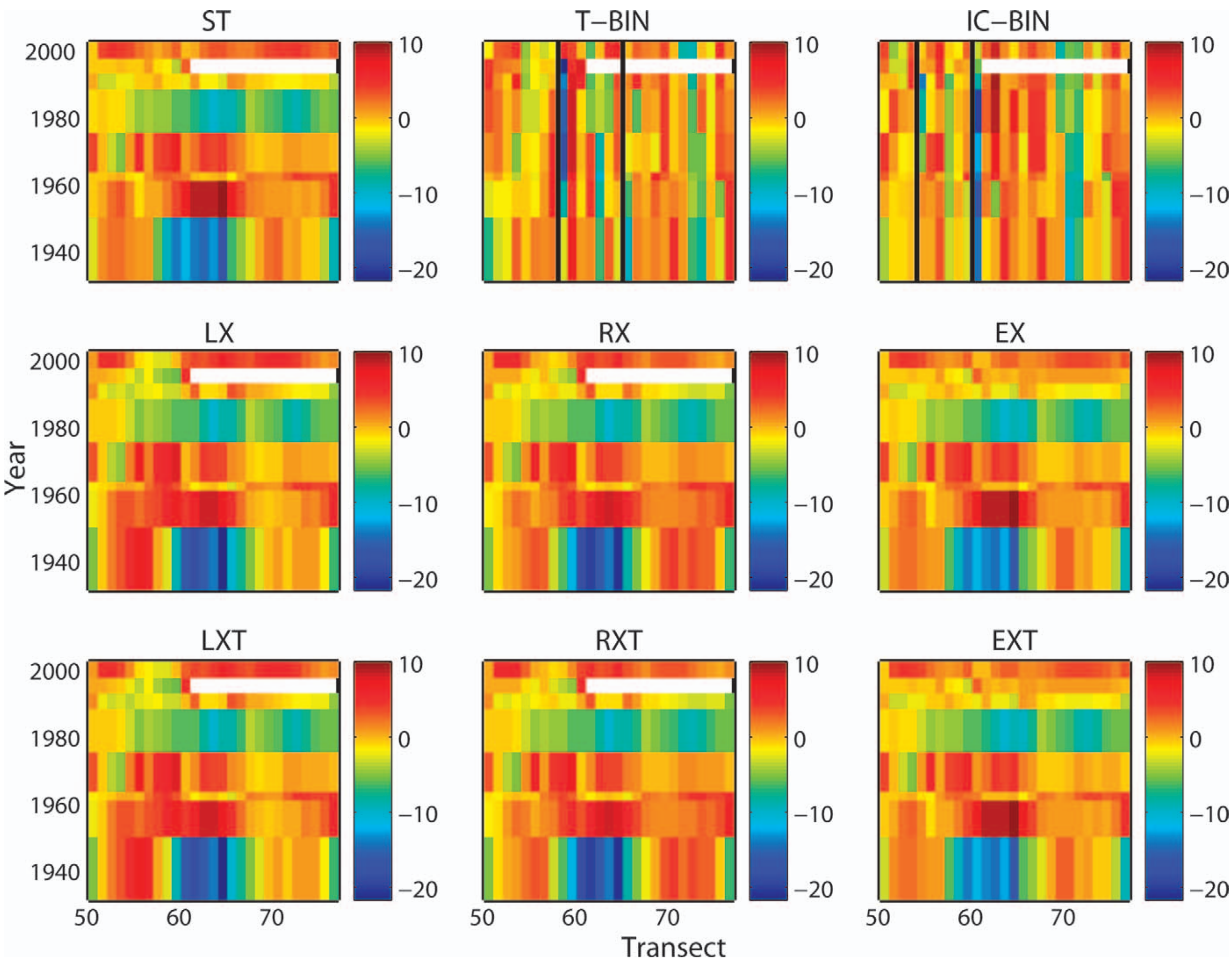

Figure 3. Color maps of residuals at Onuoli. Black lines signify the borders of IC-bin and t-bin.

Table 5. *ANOVA results of the 50-y hazard prediction. Each grouping contains methods that were not statistically different from each other at the 95% confidence interval.*

Big Beach	Kamaole 1	Onuoli	Baldwin	Kaehu	Spreckelsville	Kaanapali	Kahana	Napili
t-Bin	LXT	ST	LXT	ST	t-Bin	LX	t-Bin	ST
IC-bin	RXT	t-Bin	RXT	t-Bin	IC-bin	RX	IC-bin	t-Bin
LX	EXT	IC-bin	t-Bin	IC-bin	LX	EX	LX	IC-bin
RX		LX		LX	RX	LXT	RX	LX
LXT		RX		RX	EX	RXT	EX	RX
RXT		EX		EX	LXT	ST	LXT	EX
		LXT		LXT	RXT		EXT	RXT
		RXT		RXT	EXT			EXT
		EXT		EXT				
ST	ST		T-BIN		ST	ST	ST	
EX	T-BIN		IC-BIN			T-bin	EXT	
EXT	IC-BIN		LX			IC-BIN		
	LX		RX			EXT		
	RX		EX					
	EX		EXT					
			ST					

Fifty-Year Hazard Line

We ran an ANOVA test on the 50-year hazard predictions, from all the methods at each beach, to test whether the mean predictions of the different methods differed significantly from each other. Three of the nine beaches (including the no rates of ST) had statistically insignificant 50-year hazard lines for all nine methods at the 95% confidence level (Table 5). The hazard predictions with acceleration were significantly different from the predictions with nonacceleration methods for Baldwin and Kamaole (EXT equaled EX at Baldwin). Although Kamaole showed no significant difference between the acceleration methods, EXT deviated from predictions of the other acceleration methods, with EXT showing both higher erosion and higher accretion, but the mean value for EXT was not different from the other acceleration methods. The acceleration methods at Baldwin showed accretion for most of the beach, whereas the nonacceleration methods showed either no erosion or some erosion (Figure 4). The methods that had no rates at Big Beach and Spreckelsville were significantly different from the methods that had rates. The predictions with EXT were not significantly different from the predictions with methods that had no rates at Kaanapali and Kahana.

Figure 4. Fifty-year hazard predictions at Baldwin. LXT and RXT agreed with each other. IC-bin, t-bin, LX, RX, and EX had similar predictions (EXT reduced to EX). Single-transect had insignificant rates at this beach.

Prediction of Most Recent Shoreline

Similar to results using all shoreline data, ST had no rates for all beaches. t-Bin had no rates for seven beaches and found rates only at Baldwin and Spreckelsville. EXT indicated acceleration for three of the nine beaches, whereas LXT and RXT identified acceleration for four beaches.

LX and RX predicted the most recent shoreline the best for Big Beach (Table 6). LXT and RXT reverted to LX and RX at this beach. All other methods had no rates at Big Beach. Single-transect, t-bin, IC-bin, LX, RX, and EX had no rates at Kamaole. These methods had significantly lower mean |EIPs| than the methods that calculated rates (LXT, RXT, and EXT) at the 95% confidence level. For Onuoli, ST and t-bin had rates of zero, with significantly higher mean |EIPs| than the other methods. EX had the lowest mean |EIP|, but was not statistically significant from the mean |EIPs| of IC-bin, LX, and RX at the 95% confidence level. LXT, RXT, and EXT reverted to LX, RX, and EX at Onuoli.

Single-transect had rates of zero at Baldwin, yet had the lowest mean |EIPs|. The predictions with ST were not significantly different from predictions with LXT and RXT, both of which identified acceleration (EXT did not find acceleration). All other methods predicted higher erosion for the most recent shoreline. Single-transect and t-bin had no rates at Kaehu, yet their mean |EIPs| were similar to all other methods, excluding LXT. LXT had the highest mean |EIP|; it was the only method to identify acceleration. At Spreckelsville, no methods, except ST, had significantly different mean |EIPs|, even though RXT identified acceleration (Table 6).

At Kaanapali, ST, t-bin, and IC-bin had no rates and had the lowest mean |EIPs|. However, the mean |EIPs| were not

Table 6. *Cross-validation results. EIP = error in prediction, mean |EIP| is the average magnitude difference between the predicted and known shoreline position.*

	Mean |EIP| (m)								
	Kihei			North Shore			West Maui		
Method	Big Beach	Kamaole 1	Onuoli	Baldwin	Kaehu	Spreckelsville	Kaanapali	Kahana	Napili
ST	8.52	5.45	8.57	11.64	2.22	12.42	8.13	8.82	7.19
t-Bin	8.52	5.45	8.57	19.10	2.22	6.81	8.13	8.82	7.19
IC-bin	3.06	5.45	4.38	18.68	1.27	6.44	8.13	3.42	7.19
LX	3.29	5.45	5.01	18.56	1.43	5.07	10.70	2.52	7.19
RX	3.29	5.45	5.01	19.48	2.57	7.26	10.51	3.36	7.19
EX	8.52	5.45	3.71	18.61	1.45	7.20	8.67	3.96	6.39
LXT	3.29	12.51	5.01	13.02	3.49	5.07	10.70	5.47	7.19
RXT	3.29	12.51	5.01	13.90	2.57	8.85	10.51	5.85	7.19
EXT	8.52	16.81	3.71	18.61	1.45	7.20	8.30	3.96	6.08

significantly different from all other methods. Only EXT identified acceleration at this beach. At Kahana, ST and t-bin had no rates and the highest mean |EIPs|. LXT and RXT identified acceleration and had higher mean |EIPs| than the nonacceleration methods, which had mean |EIPs| that were not significantly different from each other. Only EX and EXT had rates at Napili, yet their mean |EIPs| were not significantly different from all the other methods with no rates (Table 6).

Synthetic Analysis

Overall, ST and t-bin had the highest IC scores (worst fits), but predictions made with ST were not greatly different from predictions made with other nonacceleration methods. t-Bin predictions were different from other nonacceleration methods when rates varied in the alongshore direction. t-Bin IC scores were highest for these synthetic data sets. EXT and LXT had the lowest IC scores (best fits) when acceleration was present in the synthetic data. When no acceleration was present, both EX and EXT had the lowest IC scores. Predictions with the acceleration methods were better than nonacceleration methods when acceleration was present and were similar to nonacceleration methods when acceleration was not present. LXT and RXT had lower mean |EIPs| than EXT, but variation between them was minimal. One possible reason EXT had higher mean |EIPs| than the other acceleration methods is that EXT uses principal components of the beach data as its basis functions, which, in this case, include noise.

Synthetic Data Set 1: Constant Rate and Acceleration in Alongshore Direction

The rate and acceleration were constant for each transect along the beach; therefore, the 50-year position did not change along the beach. Single-transect, t-bin, IC-bin, LX, RX, and EX underestimated the 50-year positions, whereas the means of the predictions with LXT, RXT, and EXT were 1 m less than the known 50-year position (Figure 5). LXT and RXT had the lowest mean |EIPs| (Table 7). All methods identified rates that were not equal to zero. Acceleration was identified for all 50 trials.

Synthetic Data Set 2: Constant Acceleration and Varying Rate in Alongshore Direction

In this synthetic data, acceleration was constant for each transect; hence, although the rate was different at each transect (it was modeled with a polynomial), the rate at which the rate changed with time was the same at each transect. T-Bin had the highest IC score for all 50 trials. EXT had the lowest IC score for 35 of the 50 trials. LXT had the lowest IC score for the other 15 trials. RXT had the lowest mean |EIP|, followed closely by LXT. EXT predictions had more variability around the known shoreline position, causing its mean |EIP| to be slightly higher than LXT and RXT. All methods identified rates that were not equal to zero, and LXT and RXT identified acceleration in all 50 trials. EXT did not identify acceleration in two trials. Predictions with ST were not different from IC-bin, LX, RX, and EX.

Synthetic Data Set 3: Constant Rate and Varying Acceleration in Alongshore Direction

In this test, the change rate was held constant along the beach but varied temporally. Single-transect and EX had rates of zero for all 50 trials. They also had the highest mean |EIPs|. t-Bin, IC-Bin, LX, and RX identified constant rates in the alongshore direction and had lower mean |EIPs| than ST and EX. LXT, RXT, and EXT all identified acceleration, with LXT having the lowest mean |EIP|.

Synthetic Data Set 4: Varying Rate and No Acceleration in Alongshore Direction

For this synthetic beach, the rates varied along the beach, but were constant with time. LXT and RXT did not allow for acceleration for 35 and 48 of the 50 trials, defaulting to LX and RX, respectively. EXT did not identify acceleration for 11 of the 50 trials. LX had the lowest mean |EIP|, followed closely by RX, ST, EX, and RXT. T-Bin had the highest mean |EIP|.

DISCUSSION

If notable changes in the shoreline occur through time, methods that test for acceleration are recommended. Based

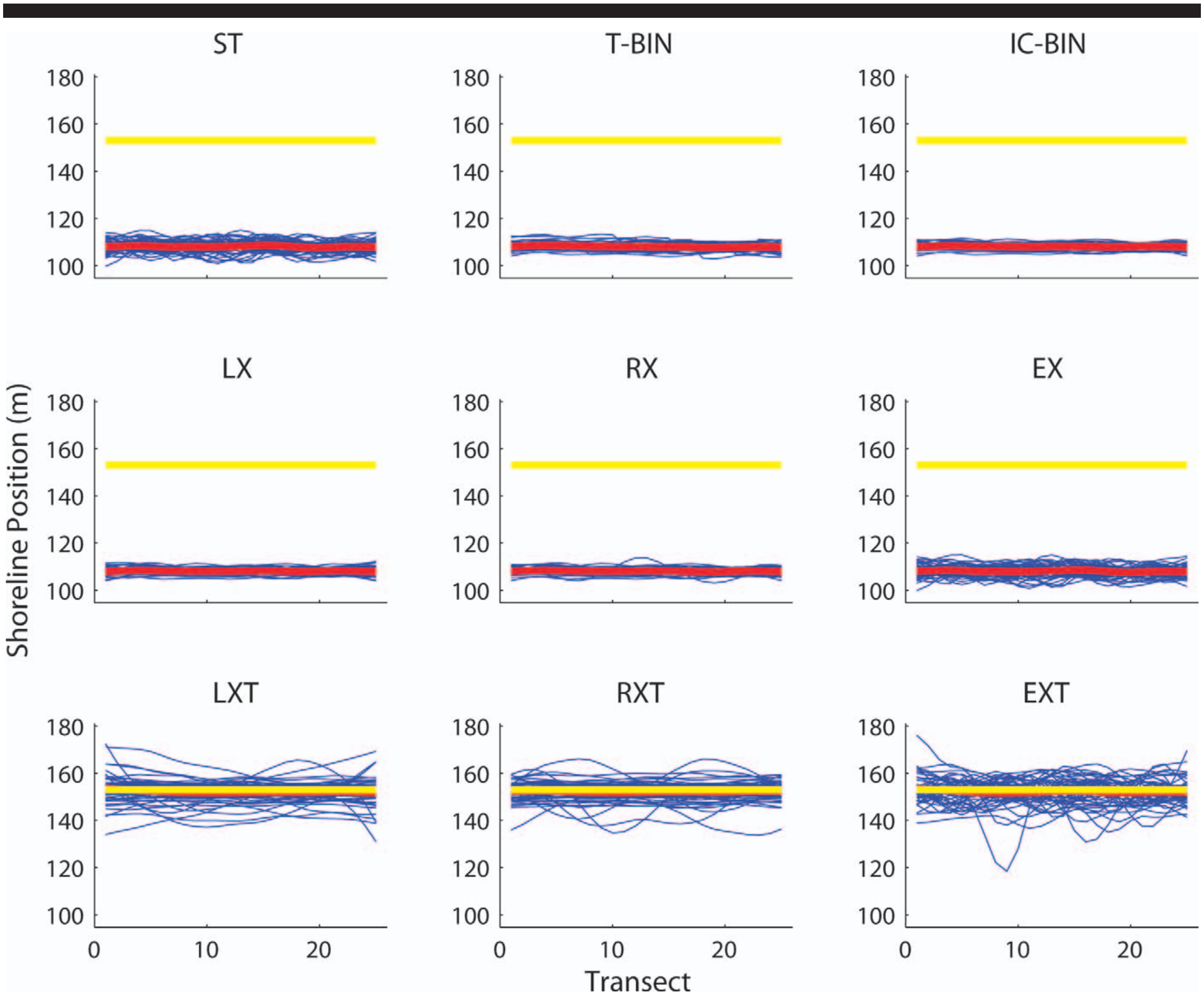

Figure 5. Fifty-year hazard predictions in the first synthetic data set of the synthetic analysis. The yellow line is the true 50-y position, the blue lines are the predicted 50-y predictions at each trial, and the red line is the mean positions of all trials.

Table 7. *Mean |EIP| results of the four synthetic data sets.*

	Mean |EIP| (m)			
Method	Run 1	Run 2	Run 3	Run 4
ST	44.91	44.92	1008.97	4.17
t-Bin	44.90	85.49	908.80	77.18
IC-bin	44.90	44.92	908.80	5.67
LX	44.90	44.92	908.80	3.69
RX	44.91	44.92	908.80	4.17
EX	44.91	44.84	1008.97	4.17
LXT	3.56	10.25	4.66	8.12
RXT	3.33	8.38	6.14	4.82
EXT	4.19	19.77	6.43	10.63

on the synthetic results, LXT, RXT, and EXT predicted the 50-year position better than all other methods. However, the cross-validation results showed that predictions with acceleration methods were not better than the nonacceleration methods (acceleration was identified at six of the nine beaches). When acceleration was identified, its predictions were generally not significantly different from either the nonacceleration methods or cases where rates equaled zero. At Baldwin, the acceleration methods were significantly better than the nonacceleration methods but were insignificantly different from ST, which had rates of zero. At Kaanapali and Napili, the acceleration methods were insignificantly different from both the nonacceleration methods and ST. At Kahana, the nonacceleration methods were significantly better than the acceleration methods. Kamaole was the only beach where rates equal to zero were better than predictions with acceleration. Although ST had rates equal to zero for all nine beaches, its predictions were not significantly different from the other methods in five beaches. In the four beaches where ST was significantly different from the other methods, the ST predictions were inferior to the other methods. Therefore, in our cross-validation study, acceleration was not always preferred but was similar to predictions made without acceleration.

One possible disconnect between the two results is that the synthetic data sets tested long-term change, and cross-validation tested short-term change. Similar to the Crowell, Douglas, and Leatherman (1997) study, using temporally rich sea-level data as a proxy for shorelines to determine how well long-term predictions fare with data that have similar noise patterns to historical shorelines might give us insight into the long-term trends of shoreline data. However, one problem with sea-level data is that it doesn't vary in the alongshore direction. To overcome this issue, known beach slopes along the shoreline (possibly extracted from lidar data) could be used in combination with the sea-level data to account for alongshore variability. The best solution, though, would be to have a more comprehensive shoreline database.

Single-transect had the highest AIC_u score for seven of the nine beaches. Single-transect failed to find rates more often than any other method. When a goodness of fit is determined from a trend with 5 to 10 shoreline positions, the signal-to-noise ratio is low. Therefore, ST will identify rates equal to zero more frequently than any other method.

The IC score always identified the model with the lowest residuals, except at Kamaole, Kaanapali, and Napili (see Tables 3 and 4). In the cross-validation study, the predictions with rates equal to zero at these three beaches were not significantly different from all other methods. These three beaches also had the highest residuals in the shoreline analysis. For these three cases, a model with no rates (as in ST) produces equal, if not better, results. Kamaole is a dynamic beach without a fringing reef, allowing the beach to undergo the full force of the wave climate, which has caused the beach to experience episodes of accretion and erosion throughout its history (Makai Ocean Engineering and Sea Engineering, 1991). Kamaole experienced kona storms in the early 1960s that caused high erosion, which resulted in a 1963 shoreline position that was more erosive than any shoreline past or present at that beach (Rooney and Fletcher, 2005). The inclusion of this shoreline decreases the goodness of fit of the model on the data. Coastal scientists have investigated and debated the impact of storm shorelines on historical shoreline analyses, and many have concluded that storms do cause short-term changes, but do not affect the long-term trend, if the shoreline recovers to its prestorm position (Douglas and Crowell, 2000; Galgano, Douglas, and Leatherman, 1998; Honeycutt, Crowell, and Douglas, 2001; Zhang, Douglas, and Leatherman, 2002). Similar to ST, binning methods, polynomial methods, and eigenbeaches are not immune to the effects of storms. Ways to overcome this are to remove the storm shoreline for the entire beach, use reweighted least squares (RWLS) to remove statistical outliers (Eversole and Fletcher, 2003; Genz *et al.,* 2007), use least absolute deviation (LAD) to downplay the influence of an outlier, or model the storm shorelines and include them in the overall shoreline-change model. All these solutions can be used in both ST and newer methods.

Kaanapali is influenced by a strong seasonal signal that affects the historical shoreline analysis. Although we try to account for seasonal changes in our uncertainty analysis, it is not enough on beaches that have strongly variable behavior. All methods showed minimal erosion, no erosion, or accretion at the northern part of the beach; however, the most recent shoreline positions in the north had eroded more than what was accounted for by all the methods. This could be because the most recent shoreline was taken in May. Kaanapali, at this time, usually starts accreting sand to the north, but the beach might not reflect the accretion in May. With strong seasonal behavior, rates of zero would explain the change more accurately than any modeled rate. Napili is a small pocket beach that is stable with minimal erosion; only EX and EXT had rates that were not equal to zero. Although the predictions with EX and EXT were better than the methods with rates equal to zero, the predictions between all methods were not significantly different, with a difference of $\sim$1 m (Table 6).

Baldwin is the only beach where acceleration methods predicted the most recent shoreline significantly better than the nonacceleration methods. However, ST had insignificantly different predictions when compared with the acceleration methods (ANOVA). Dramatic erosion took place between 1912 and 1960, followed by either minimal erosion or accretion after that. The deceleration in the erosion rate was severe enough that the acceleration methods were able to model the shoreline with greater accuracy than the nonacceleration methods. Single-transect identified no rates at this beach, which is compatible with the decrease in erosion rate found with the acceleration methods. Therefore, ST predictions for this beach were insignificantly different from methods with acceleration. Other beaches do identify acceleration, but predictions with acceleration methods are either insignificantly different or significantly worse than the nonacceleration methods. One reason could be that the acceleration is minimal and the nonacceleration methods are sufficient at predictions of 5–7 years (cross-validation).

Based on synthetic results, LXT, RXT, and EXT outperformed the nonacceleration methods. When acceleration was not present in the synthetic data, EXT identified acceleration for 39 of the 50 trials, whereas a majority of RXT and LXT synthetic data sets did not, and reverted to RX and LX. EXT, in this case, modeled the noise. Although noise might influence EXT more than the other methods, its mean |EIPs| were only $\sim$2 m different from LXT (Table 7). The advantage of including unknown beach physics in the EXT model supersedes the effects of noise on this method. In all other synthetic data sets where acceleration was present, nonacceleration methods did not predict the future hazard position as well as the acceleration methods. Considering that the acceleration methods did reduce to the nonacceleration methods in most trials when acceleration was not present and that the acceleration methods predicted the 50-year position better than the nonacceleration methods when acceleration was present, we conclude that the acceleration methods are able to

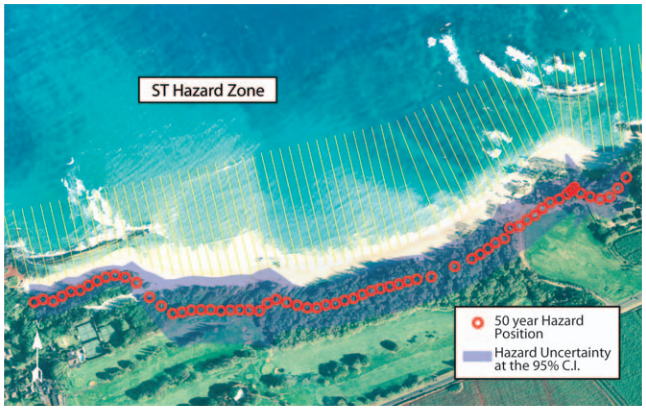

Figure 6. Hazard zone of single-transect at Baldwin. The 50-y hazard position (red circle) is surrounded by uncertainty bands (blue zone) at the 95% confidence interval.

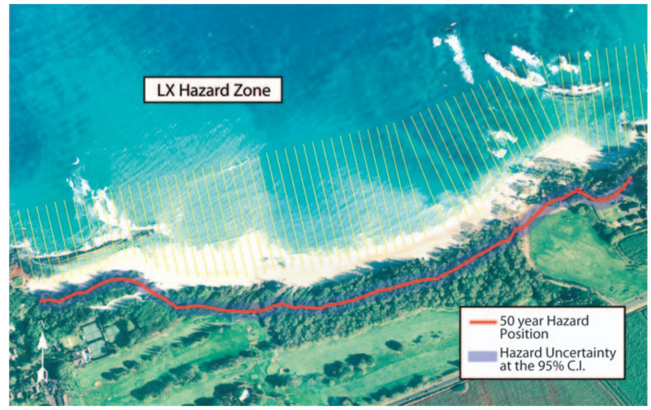

Figure 7. Hazard zone of LX at Baldwin. The 50-y hazard line (red line) is surrounded by uncertainty bands (blue zone) at the 95% confidence interval.

predict the 50-year position more accurately than the other methods.

Acceleration

Many scientists have recognized the problems with implementing linear regression (*e.g.,* Crowell, Douglas, and Leatherman, 1997; Douglas, Crowell, and Leatherman, 1998; Fenster, Dolan, and Elder, 1993; Galgano, Douglas, and Leatherman, 1998). One often-noted drawback is the assumption that a beach erodes at a constant rate. Quasiperiodic variation on a seasonal or decadal span, as well as major storms, can either accelerate or decelerate erosion on beaches (Crowell, Douglas, and Leatherman, 1997; Douglas, Crowell, and Leatherman, 1998; Galgano, Douglas, and Leatherman, 1998; ; Morton, Gibeaut, and Paine, 1995; Zhang, Douglas, and Leatherman, 2002). Morton, Gibeaut, and Paine (1995) concluded that acceleration and deceleration were needed to accurately model future shoreline positions. Fenster, Dolan, and Elder (1993) tried to address this problem by fitting nonlinear trends to shoreline positions at individual transects using a different version of the minimum description length statistic (MDL) equation. As each transect contains limited data points, and high percentages of linear fits at individual transects are statistically insignificant, the resulting nonlinear fit would be an overparameterization of the data. Fenster, Dolan, and Elder (1993) recognized this issue and adopted a two-line system—the low-weight line and the zero-weight line, leaving the choice of which line to use up to the analyst. However, Crowell, Douglas, and Leatherman (1997) showed that results from the Fenster, Dolan, and Elder (1993) method were not superior to simple linear regression.

LXT, RXT, and EXT allow acceleration or deceleration; however, these methods prevent overparameterization by modeling all transects within a beach system simultaneously. In our analysis with all shoreline positions, EXT identified acceleration in four of the nine beaches, LXT identified it in three beaches, and RXT only found acceleration in two beaches. When acceleration was present for all three methods, the results generally concurred with each other. As each method uses different basis functions to identify acceleration, the good agreement between them is striking. One problem with these methods is that short-term predictions of known shorelines are more variable than predictions using methods with no acceleration.

Hazard Zones

Most remote-sensing software can project hazard zones on aerial photogrammetry. These hazard zones can aid in establishing construction setbacks. Figures 6–8 (ST, LX, and LXT) depict 50-year hazard lines with their uncertainties at the 95% confidence interval at Baldwin. The hazard zones are based on rates of the different methods. Single-transect had no significant rates because it identified no rates for all beaches. The new methods had, on average, significant rates at 74.62% of all transects.

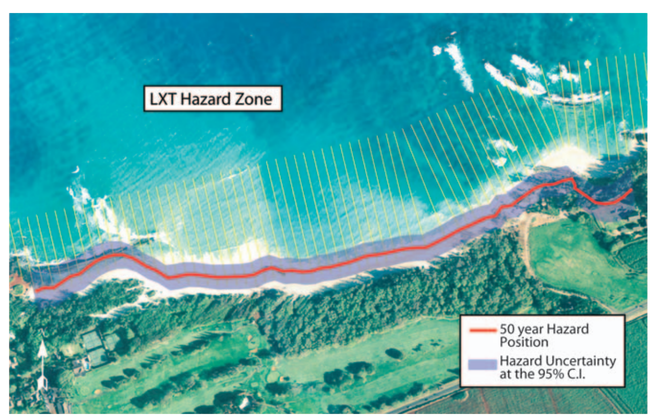

Figure 8. Hazard zone of LXT at Baldwin. The 50-y hazard line (red line) is surrounded by uncertainty bands (blue zone) at the 95% confidence interval.

CONCLUSIONS

Hazard maps can be used to identify possible hot spots of erosion and to implement preventative measures, such as setbacks. Therefore, it is important to use methods that produce statistically defensible results. Single-transect had a higher chance of identifying rates equal to zero, making the rates insignificant. Nonacceleration methods predicted short-term positions best, and acceleration predicted long-term changes using synthetic data best. Acceleration methods did well when shoreline positions had prominent shifts through time and should be used for these cases. Long-term predictions need to be more thoroughly investigated by cross-validating a known position using either a large shoreline database or a database that can be used as a proxy to shoreline data (*e.g.,* sea-level data).

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