

IMPROVING STATISTICAL VALIDITY IN CALCULATING EROSION HAZARDS FROM HISTORICAL SHORELINES

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Abstract: We evaluate three classes of shoreline change rate methods on all sandy beaches of Maui: 1) methods that estimate shoreline change transect by transect, 2) methods that combine data from all transects to estimate shoreline change, and 3) extensions of (2) that include acceleration. Using these, we compare 50 yr hazard zones from beaches exposed to different conditions, natural beaches versus altered beaches, and well-defined littoral cells versus open systems. Acceleration methods fit the data well, but don't predict the erosion hazard zone well. Altered beaches and open system beaches are better fit by methods with acceleration at a higher proportion than natural or pocket beaches. The traditional transect by transect method that calculates shoreline change at discrete points along a beach never qualifies as the best fit model.

INTRODUCTION

Historical shorelines are commonly extracted from aerial photographs and NOAA topographic surveys (T-sheets). They are generally limited and spaced unevenly through time. Currently the most common shoreline change method is the single-transect (S-T) method. S-T uses data from individual shore-normal transects to calculate shoreline change rates. As there are only 5-10 shorelines at each transect, the resulting rates are often uncertain. The equation for S-T at each transect is:

$$y_j - \bar{y} = (t_j - \bar{t})r + n_j \quad (1)$$

where y_j is the shoreline position at time t_j , \bar{y} is the baseline, \bar{t} is the time origin, r is the change rate, and n_j is the noise. As the baseline has been chosen to give a zero intercept, there are effectively two model parameters for each transect. For a beach with I transects, the S-T method requires $2I$ parameters.

Genz *et al.* (in press) recently introduced binning (hereinafter, T-binning) as a new method that improves the significance of fit and lowers uncertainties. T-binning combines transects with rates that are insignificantly different and calculates one rate for each bin. Grouping transects requires heavy user input that can bias results. Frazer *et al.* (in review) improve on T-binning by removing user input. Called A-binning, transects are binned using the corrected Akaike Information Criterion (AICc) to identify best groupings. However, computation-time increases rapidly with the number of bins. In both T-binning and A-binning, change rate is discontinuous at bin boundaries.

Frazer *et al.* (in review) also introduced the PX method (think: polynomial in x), an alternative to binning and single-transect that makes change rate continuous along a beach. The PX method fits transect measurements to the following equation,

$$y_{ij} - \bar{y}_i = \sum_{k_0=0}^{K_0} \alpha_{k_0}^{(0)} P_{k_0}(z(x_i)) + (t_j - \bar{t}) \sum_{k_1=0}^{K_1} \alpha_{k_1}^{(1)} P_{k_1}(z(x_i)) + n_{ij} \quad (2)$$

in which \bar{y}_i is the baseline at transect i , the x_i are the transect locations, $z(x)$ is a mapping from alongshore distance to the interval $[-1,1]$, the $P_k(z)$ are basis functions (e.g., Legendre polynomials), the α_k are coefficients, and n_{ij} is noise. A well chosen baseline causes all the coefficients in the first sum to vanish, hence the number of parameters in the model is $I + K_1$, where I is the number of transects.

After the coefficients have been found, the second sum on the right hand side of equation (2) gives the change rate of the beach at time \bar{t} . Frazer *et al.* (in review) suggested three types of basis functions for use in PX, denoting PX by LX when Legendre polynomials are used, by RX when trigonometric functions are used, and by EX when empirical orthogonal functions of the beach data are used (Table 1). The motivation for EX is that, if the beach physics can be represented by a linear system, the beach at any instant in time must be a linear sum of the eigenfunctions of a linear operator.

To allow for a rate that changes with time, the right hand side of equation (2) can be augmented with an acceleration term,

$$\frac{(t_j - \bar{t})^2}{2} \sum_{k_2=0}^{K_2} \alpha_{k_2}^{(2)} P_{k_2}(z(x_i)) \quad (3)$$

If the acceleration term is present, the PX method is referred to as PXT, since the rate is changing with time. Similar to PX, PXT is divided into three methods according to their basis functions – LXT, RXT, and EXT (Table 1). Genz *et al.* (in review) compared PXT to other methods and found PXT to be more erratic in predicting known positions.

Table 1. Description of Methods

Method	Basis Functions	Acceleration?
S-T	---	no
LX	Legendre polynomial	no
RX	Trigonometric functions	no
EX	Eigenvector of beach data	no
LXT	Legendre polynomial	yes
RXT	Trigonometric functions	yes
EXT	Eigenvector of beach data	yes

In the expressions above, the upper limits K_1 and K_2 can be as large as the number of transects I , so there are I possible PX models and I^2 possible PXT models. Of interest here is the fact that if lower order basis functions are selectively included or omitted, the number of possible PX models increases to 2^I , and the number of possible PXT models increases to 2^{2I} . By testing all combinations, a better-fit model may be obtained. In this paper we use synthetic data to investigate the omission of lower-order terms.

Fletcher *et al.* (2003) calculated shoreline change using S-T for all sandy beaches of Maui. They used Reweighted Least Squares (RLS) to determine shoreline change at each transect. We also calculate shoreline change on all sandy beaches of Maui by predicting the 50-yr hazard zone. We compare S-T, LX, RX, EX, LXT, RXT, and EXT. Our study is motivated by the assumption that when different models predict similar hazard zones, the predicted hazard zones are more reliable.

EXCLUSION OF LOWER-ORDER TERMS IN PX AND PXT

If lower order terms in equations (2) and (3) can be selectively omitted, comparing the AICc score of all possible PX and PXT models is impractical. For example, if there are 25 transects on a beach, all possible PX models would equal 2^{25} , or 33,554,432. All possible PXT models would equal $2^{(2*25)}$, or 1.13×10^{15} . At present, computers are too slow to calculate every possible combination in a timely manner, so usually we do not calculate all possible combinations for PX and PXT; we include all lower-order terms basis functions when calculating higher order polynomials. However, Genz *et al.* (in review) show inconsistent hazard predictions using PXT. This leads us to investigate whether the exclusion of lower-order terms might improve the 50 yr hazard prediction. One way to test a large number of models is by using genetic algorithms (GA). Goldberg (1989) has an excellent explanation of GAs, which we briefly summarize: As the name indicates, genetic algorithms are based on biological ideas of natural selection. Any GA begins with a population of models, coded as strings; each string can be thought of as an individual organism with a single chromosome, and each parameter in the model can be thought of as a gene. Each string has a “fitness” based on how well it fits the data. Fitter strings are passed on to the next generation; thus, each generation evolves from the previous generation, and the best-fit string(s) are found after many generations. In our

application, each string is a binary number with number of bits equal to the number of possible basis functions in the model. Each bit corresponds to a particular basis function. If the first bit is a zero (one) the lowest order basis function is excluded (included) in the model, and so forth. The fitness value of a string is the fitness of the best-fit model with the permitted basis functions.

Each generation is produced by *selection*, *crossover*, and *mutation* of the previous population. Selection is based on the fitness function; a string with higher fitness function has a better chance of being selected. Crossover occurs between pairs of strings that have undergone selection. Each pair is cut at the same location and string segments are swapped to make a new pair. The final, and less important, operation is mutation, whereby the value at each location on a string has a very low probability of being switched from zero to one or vice-versa.

In the shoreline scenario of a beach with 25 transects, we use a Matlab GA to determine the optimal combination of terms for both PX and PXT. In an initial generation with a population size of 100, there are 100 strings, each with a different combination of coefficient terms. The fitness function is the negated AICc score. By specifying the number of generations and acceptable tolerance limits, we can efficiently identify the combination of coefficient terms. Figure 1 is an example of output from a GA in MATLAB.

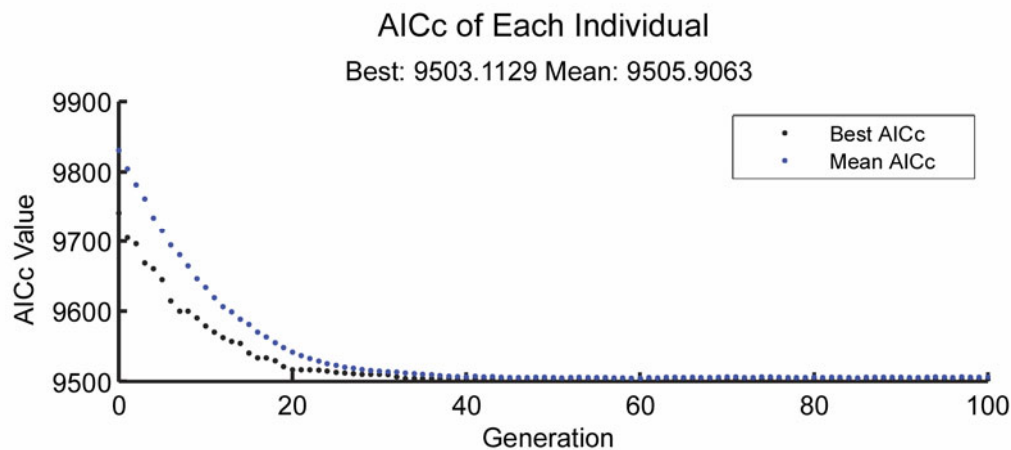


Fig. 1. Example of a Genetic Algorithm (GA) with a population size=100 and a limit of 100 generations.

MAUI SETTING

The sandy beaches of Maui Island form three regions: Kihei, West Maui, and North Shore (Figure 2). Each region is exposed to different wind and wave regimes (Fletcher *et al.*, 2003; Rooney *et al.*, 2003). Kihei is protected by the islands of Molokai, Lanai, Kahoolawe and is subjected to refracted North Pacific swell, south swell, and Kona storm waves (Rooney and Fletcher 2005). Kona is a low-pressure system that creates winds and waves from the south. West Maui is affected by North Pacific swell, Kona storms and south swell (Eversole and Fletcher 2003). The North Shore is strongly affected by

the north swell, and tradewind waves (Fletcher *et al.*, 2003; Makai Ocean Engineering and Sea Engineering 1991; Rooney *et al.*, 2003).

Each beach is classified into one of five categories, based on whether the beach has hardened structures (Table 2). The first classification includes beaches with hardened structures where no backshore fronts the structures. These beaches are severely impacted. If enough shoreline data exists, then only post-hardened shorelines are used to predict the 50 yr hazard zone. If shoreline data are sparse, then pre-hardened shorelines are used to identify beach change without predicting the 50-year hazard zone. Including both pre- and post-hardened shorelines in an analysis violates the underlying assumption of the change rate methods, which is that beach physics are constant.

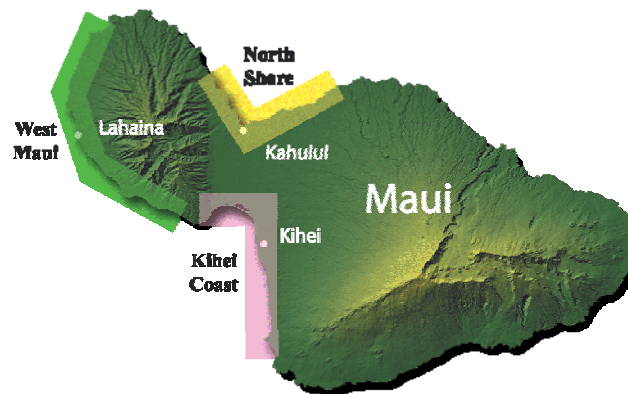


Fig. 2. Three regions of Maui

If a backshore exists in front of hardened structures, we assume the beach is not impacted and all shorelines are used for the analyses. If a beach experienced direct impact (e.g., beach nourishment), then a 50 yr hazard zone is not predicted. If the beach appears to be unaltered by hardened structures (natural), then a 50 yr hazard zone is predicted using all shorelines.

Using the classification scheme, there are 30 natural beaches and 46 hardened beach segments on Maui (Table 3). The 50 yr hazard zone is not calculated for two beaches (classified as category #2 and #4). We do not include these two beaches in our analysis.

Table 2. Beach Classification

Category	Hardened Shoreline?	backshore present?	Hazard Zone Predicted?
1	yes	no	yes
2*	yes	no	no
3	yes	yes	yes
4**	yes	yes	no
5	no	--	yes

* not enough post-hardened data

** excessive human interference

Of the 74 beaches, 27 have well-defined borders (pocket beaches), and 17 have ill-defined borders (open system beaches). Fourteen beaches are actually segments of longer beaches since hardened structures (i.e., groins) serve as borders for these areas. These beaches are not included in the definition of pocket or open system beaches.

Table 3. Maui Beach Breakdown

Category	Kihei	West Maui	North Shore	Total
1	4	13	5	22
2	1	0	0	1
3	5	2	15	22
4	0	0	1	1
5	11	13	6	30
Total	21	28	27	76

METHODS

Our methodology includes two distinct procedures. The first is to test the exclusion of lower-order terms with GAs. The second is to calculate the 50 yr hazard zone for all sandy beaches on Maui.

Using the genetic algorithm

Synthetic data are used to compare the GA process (testing randomly up to 2^{2l}) with the limited iterative process (testing up to I^2) by predicting a known 50 yr hazard line. We calculate the hazard line for the PX methods (LX and RX) and the PXT methods (LXT and RXT). EX and EXT are excluded from this analysis because the number of possible models is limited by the number of shoreline years (Frazer et al., in review). The synthetic data has 100 transects, a 3 m intercept, an alongshore rate modeled by a quadratic polynomial, and a constant acceleration that equals 0.01 m/yr/yr. The noise is sampled from a Gaussian distribution with zero mean. We repeat experiments using noise processes with different standard deviations. The first experiment has a standard deviation of 1.95 m, which is based on the root mean squared error of a PX fit at an actual beach in Maui. Successive experiments have noise processes with standard deviation equal to 5, 10, 25, 50, 100, and 250 m.

50 yr Hazard Zone

For the 74 beaches, we calculate a 50 yr hazard position using S-T, LX, RX, EX, LXT, RXT, and EXT. We omit the binning methods, as Genz et al. (in review), found that results from A-binning and T-binning were insignificantly different from LX, RX, and EX on these beaches. All methods utilize Weighted Least Squares (WLS) to calculate misfit. The 50 yr hazard zone is the 50 yr position with a 2σ (95%) uncertainty band. We calculate the AICc score for each beach to determine which method best fits that beach. We also apply an ANOVA test on the 50-yr hazard prediction to determine whether the resulting predictions from all methods are significantly different or not.

RESULTS

Within Maui beaches, 9 of 22 beaches with hardened structures have only 3 shorelines (category 1, Table 2). Although there are more shorelines at these beaches, hardened structures dominate the beaches starting in 1975. Because 3 shorelines are not enough to

make sizeable predictions (such as the 50 yr hazard position), we remove these beaches and report the results of the remaining 65 beaches.

Genetic algorithms

For all noise processes, predictions using GA and predictions using the limited iterative process were similar (Figures 3 and 4). Figure 3 illustrates the GA 50 yr hazard predictions compared to the 'true' hazard line determined using synthetic data. Figure 4 illustrates the limited iterative process hazard predictions compared to the 'true' hazard line. LXT identifies acceleration in all but one experiment (LXT does not identify acceleration in the limited iterative process when the noise has a standard deviation of 500). RXT never identifies acceleration and equals RX in both the GA and limited iterative process. RX/RXT is more variable than LX and LXT. For both sets of predictions, LXT is closest to the 'true' position when the standard deviation of the noise is less than 100. As noise increases, LX is more consistent than LXT.

Allowing lower-order basis functions to be excluded does not reduce the variability associated with the PXT methods, as the results are consistent between GA and the limited iterative process. However, the AICc values of all methods are slightly lower with the GA.

Maui Hazard Zones

Based on the AICc scores, acceleration methods were the best methods for 48 beaches (Table 4). AICc identified EX, LX or RX as the best method for 17 beaches. For all 17 beaches, EXT, LXT, and RXT did not identify acceleration (i.e., EXT, LXT, and RXT equaled EX, LX, and RX, respectively). AICc did not identify S-T as the best method for any beach. Of the 65 beaches, 83.1% of the beaches had insignificant S-T rates.

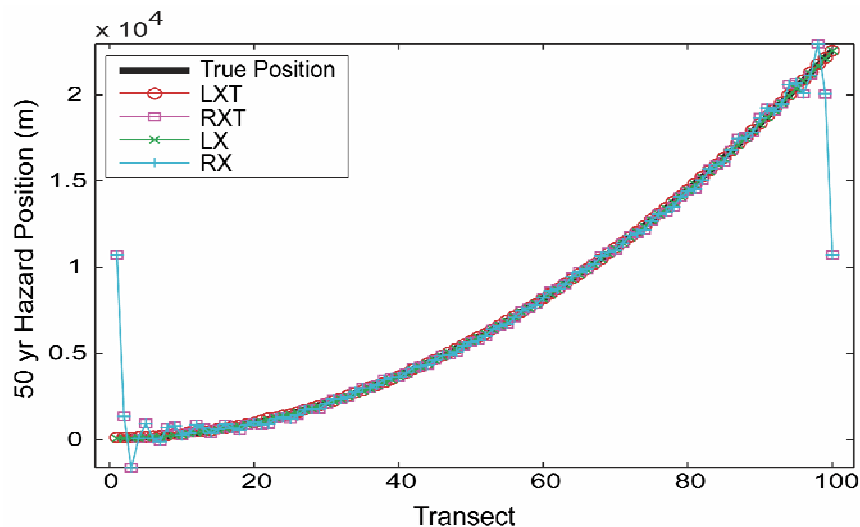


Fig. 3. GA, 50 yr hazard predictions with noise process standard deviation = 10 m.

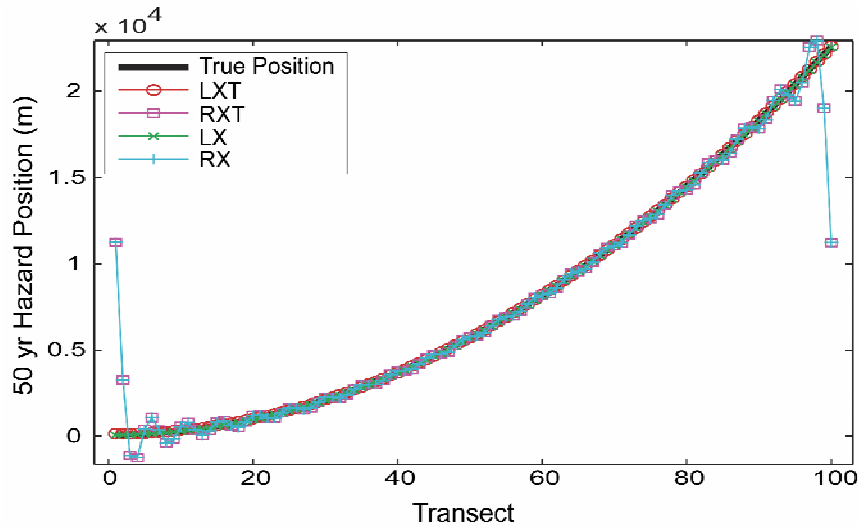


Fig. 4. Limited iterative process, 50 yr hazard prediction with noise standard deviation = 10 m.

Table 4. Number of Beaches Identified by AICc

		Method	Kihei	West Maui	North Shore	Total
Acceleration Methods		EXT	13	11	14	58.5%
		LXT	2	3	1	9.2%
		RXT	2	1	0	4.6%
		LXT ≈ RXT	1	0	0	1.5%
Non- Acceleration Methods		LX ≈ RX	1	2	1	6.2%
		EX	1	3	6	15.4%
		LX ≈ RX ≈ EX	0	1	2	4.6%
		S-T	0	0	0	0.0%

Table 5 reports AICc results of natural beaches and hardened beaches. Hardened beaches tend to identify acceleration more than natural beaches (77.1% hardened beaches vs. 70.0% natural beaches); while natural beaches tend to identify non-acceleration methods more than hardened beaches (30.0% natural beaches vs. 22.9% hardened beaches).

Table 5. Number of Beaches Identified by AICc

		Method	Natural Beaches	Hardened Beaches
Acceleration Methods		EXT	14	24
		LXT	5	1
		RXT	2	1
		LXT ≈ RXT	0	1
		Total	70.0%	77.1%
Non- Acceleration Methods		LX ≈ RX	4	0
		EX	4	6
		LX ≈ RX ≈ EX	1	2
		S-T	0	0
		Total	30.0%	22.9%

Acceleration is recognized in 63.0% of pocket beaches, while 37.0% have no acceleration (Table 6). Open systems tend to pick acceleration methods at a much higher percentage (94.1%) than pocket beaches. S-T is not identified as the best method in any of these beach systems.

Table 6. Number of Beaches Identified by AICc

		Method	Pocket Beaches	Open System Beaches
Acceleration Methods		EXT	13	11
		LXT	2	3
		RXT	1	2
		LXT \approx RXT	1	0
		Total	63.0%	94.1%
Non- Acceleration Methods		LX \approx RX	4	0
		EX	5	1
		LX \approx RX \approx EX	1	0
		S-T	0	0
		Total	37.0%	5.9%

An ANOVA test is calculated to identify whether the means of 50 yr hazard positions are significantly different. Three main categories emerge as dominant groupings of methods (Table 7). Predictions from all methods are insignificantly different from each other in 36.9% of the beaches. Seven of these beaches have deceptive results because LXT, RXT, and EXT have extreme erosional/accretional predictions that cancel out when the mean is calculated (e.g., Figure 5). S-T was not distinguishable from LX, RX and EX in 24.6% of the beaches. S-T, the PX methods and the PXT methods were significantly different from each other in 18.5% of the beaches.

The hazard zone is composed of the 50 yr hazard position plus an uncertainty band at the 95% confidence interval. Looking at the uncertainty associated with the hazard position, S-T has the highest uncertainties for 31 beaches (Table 8). LXT, RXT, and EXT also have high uncertainties. EX has the lowest uncertainties for 48 beaches.

TABLE 7. ANOVA Results of Hazard Positions

Method Groupings		Kihei	# of Beaches		Total
			West Maui	North Shore	
1	All Methods	5	6	13	36.9%
2	S-T LX \approx RX \approx EX LXT \approx RXT \approx EXT	3	5	4	18.5%
3	S-T \approx LX \approx RX \approx EX LXT \approx RXT \approx EXT	9	3	4	24.6%

LX and RX also have low uncertainties. LXT, RXT, and EXT have the lowest uncertainties for 25 beaches (highlighted in Table 8). None of these 25 beaches identify

acceleration, hence, in this case LXT, RXT, and EXT equal LX, RX, and EX, respectively.

Table 8. Mean Hazard Uncertainty

Method	# Beaches with Lowest Uncertainty	# Beaches with Highest Uncertainty
S-T	2	31
LX	15	0
RX	13	0
LXT	8	12
RXT	6	21
EX	48	1
EXT	11	6

DISCUSSION

In all beaches, hazard predictions with LX, RX, and EX are always in agreement. These methods also have the lowest hazard position uncertainties. Genz *et al.* (in review) showed that these methods, along with binning, predict known positions more accurately than other methods. With that in mind, and with the consistency shown with these methods in all beaches of Maui, we currently advocate the use of these methods.

Although AICc identifies acceleration in 73.8% of the beaches, Genz *et al.* (in review) showed that predictions of known positions with these methods are inconsistent. AICc finds the best fit model so it is possible that acceleration models fit the data better, but do not enhance predictions. As shown by the GA results, excluding polynomials with lower-order terms did not significantly improve predictions; this is fortunate, as calculations with GA have significantly longer run times than those with the limited iterative process. More research on acceleration methods may be necessary for better predictions.

Beach Comparisons

LX, RX, and EX are identified by the AICc in pocket beaches at a higher proportion than in open system beaches. Compared to open system beaches, pocket beaches are smaller, with defined borders, such as headlands, that restrict sediment movement (Woodroffe 2002). Thus, open system beaches are more influenced by changes, such as interruptions to longshore sediment transport. Acceleration methods better account for the influx and outflow of sediment in open systems; hence 94.1% of these types of beaches show acceleration.

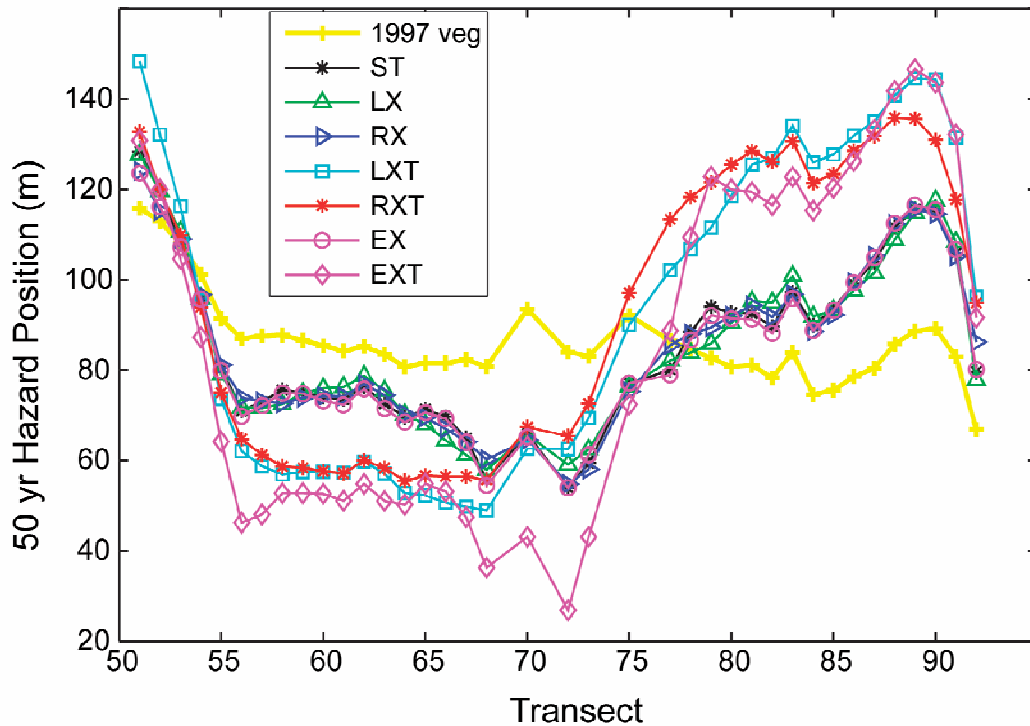


Fig. 5. 50 yr Hazard Predictions

Hardened shorelines fit a slightly higher percentage of acceleration methods than natural shorelines. Although it is a minimal difference, acceleration might be favored in hardened shorelines due to structures causing rates to vary with time. Other factors, such as storms, could influence the high frequency of acceleration found in natural beaches.

Hardened Shorelines

An important assumption of all shoreline change methods is that beach physics remain stable through the time period of interest (Fenster *et al.*, 1993; Morton 1991). Hardened structures and storms are common influences on beaches that violate this assumption. Fenster *et al.* (1993) recognized the impracticality of the change-rate methods on beaches that have undergone structural changes and introduced the Minimum Description Length (MDL) method to minimize violations of this assumption. They proposed fitting higher-order polynomials at each transect to determine the erosional trend shift and using data after the trend shift to predict future hazard positions. However, there might not be enough data to fit a higher-order polynomial at each transect.

It is important to have as long a temporal span as possible to reduce the effects of noise on the long-term trend (Crowell *et al.*, 1993). However, changes such as hardened structures and storms affect the resulting trends of a beach. Many have argued that removing storm-influenced shorelines from long-term rate analysis is valid because post-storm shorelines eventually recover to their pre-storm positions and therefore do not affect the long-term rate (e.g., Crowell *et al.*, 1993; Douglas and Crowell 2000; Galgano *et al.*, 1998; Zhang *et al.*, 2002). Unlike storms, the addition of hardened structures does affect the long-term trend. Removal of post-hardened shorelines in change-rate analysis

would only give predictions based on natural beaches. However, removal of pre-hardened shorelines would result in predictions based on beach behavior with the involvement of structures.

We addressed hardened structures in the following way: If hardened structures were present, and no backshore existed in front of the beach, we removed pre-hardened shorelines (Category 1, Table 2). However, where a backshore persisted in front of a hardened structure, we interpreted the structure as having little influence on beach dynamics, and we included the hardened beaches in our analysis (Category 3, Table 2).

AICc

Nine beaches have three shorelines and are all classified as category 1, which signifies hardened shorelines (Table 2). Only 3 shorelines are utilized in all 9 cases, with RXT identified as the best method for 3 beaches, LXT identified as the best method for 4 beaches, and S-T identified as the best method for 2 beaches. RXT, LXT, and S-T have the lowest AICc scores in these situations because the equation for AICc fails. Burnham and Anderson (2002) present the AICc equation as:

$$AICc = N \log(RSS/N) + \frac{2KN}{(N - K - 1)} \quad (4)$$

Where RSS is the residual sum of squares, N is the sample size, and K is the number of parameters. The value of the first half of equation (4) decreases as RSS decreases. The second half of equation (4) is a correction factor that increases as the number of parameters increase. This factor should always be positive in order to penalize the use of extra parameters. Thus, AICc is a tradeoff between the goodness of fit and the number of parameters, preventing over- or under-fitting of the data. However, if $K \geq N$, the correction factor in equation (4) is a large negative number. As the best-fit model is the lowest AICc score, a large negative number leads to nonsense results. This situation occurs for LXT, RXT, and S-T when ≤ 3 shorelines exist. LX, RX, EX, and EXT are not affected by this issue because K is never greater than or equal to N .

If the beach has ≤ 3 shorelines, LXT, RXT, and EXT should not be used. These methods identify whether rates are changing with time at each transect (Figure 6). Fitting a quadratic model on 3 points is over-fitting, so non-acceleration methods should be used if only 3 shorelines exist.

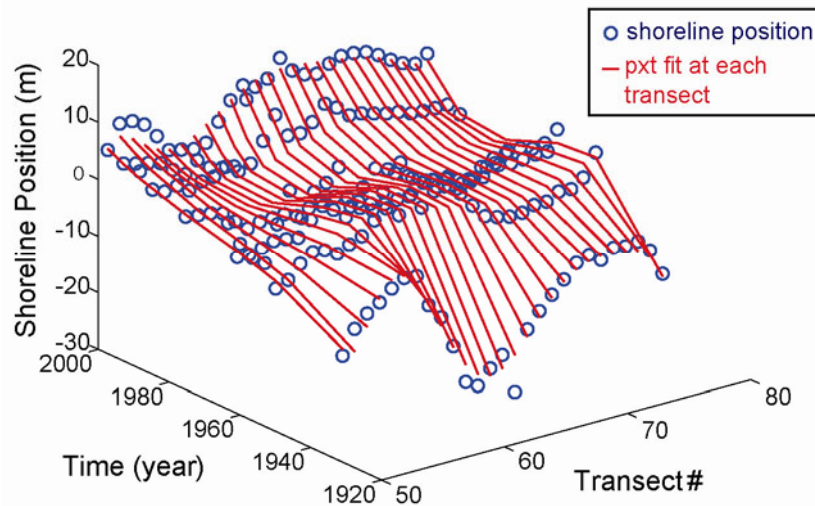


Fig. 6. Rates Changing With Time at Each Transect (PXT)

CONCLUSIONS

Overall, predictions from RX, LX, and EX are insignificantly different from each other and are recommended for use in hazard zone predictions. Predictions using polynomials without lower-order terms are consistent with predictions using all lower-order terms. LXT, RXT, and EXT appear to need more research. Ideally, the more shorelines that are available, the better the hazard predictions are. If, however, beaches have hardened structures without any backshore present in front of the structures, then only post-hardened shorelines should be used to predict future hazard zones. If there are ≤ 3 shorelines, the AICc equation does not function properly for LXT, RXT, EXT, and S-T. Both pocket beaches and open-system beaches identify acceleration methods at a higher percentage than non-acceleration methods. Still, pocket beaches identify non-acceleration methods at a higher proportion than open-system beaches possibly due to less variability in sediment transport in pocket beaches.

ACKNOWLEDGEMENTS

Funding for this research was provided by the U.S. Geological Survey, the University of Hawaii Sea Grant College of the National Oceanographic and Atmospheric Administration, Maui County Planning Department, Kauai County Planning Department, and the City and County of Honolulu. We thank members of the University of Hawaii Coastal Geology Group for their assistance.

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