Journal of Coastal Research	17	3	721–730	West Palm Beach, Florida	Summer 2001

Shoreline-Position Forecasting: Impact of Storms, Rate-Calculation Methodologies, and Temporal Scales

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ABSTRACT

HONEYCUTT, M.G., CROWELL, M., and DOUGLAS, B.C., 2001. Shoreline-Position Forecasting: Impact of Storms, Rate-Calculation Methodologies, and Temporal Scales. *Journal of Coastal Research,* 17(3), 721–730. West Palm Beach (Florida), ISSN 0749-0208.

Despite the considerable research that has sought to describe past and predict future shoreline change, little consensus has emerged on the best methodology for forecasting future shoreline positions. While a certain degree of heterogeneity in approach is warranted given the variability in coastal geomorphology and sediment-transport processes, the prediction error associated with each method has not been evaluated in great detail.

In this study, measured shoreline positions from Delaware and New York were used to calculate long-term erosion rates and make predictions to subsequent, known positions. Rates were calculated using end-point and linear-regression methods, including and excluding storm-specific shorelines. Those rate computations that included storm-specific shorelines yielded consistently poor predictions (average factor-of-three increase in error) compared with non-storm erosion rates, regardless of rate-calculation method. Linear-regression predictions, on average, performed better than end-point rate predictions, reducing error by over 70% in New York and 34% in Delaware for rates including storm shorelines, and between 4 and 31% for non-storm data (DE and NY, respectively). Predictions (hindcasts) were also made to 19th century shoreline positions using rates computed with modern, non-storm data. The positions predicted along relatively undeveloped stretches of the coast were within the 95% confidence interval associated with the prediction. Hindcasts made in areas characterized by heavy development and/or beach nourishment projects were poor, as would be expected given the recent alteration of the natural sediment-supply system. For all locations, inclusion of 19th century data reduced uncertainty in forecasts of 21st century shoreline positions by roughly 44%. These results show that forecasts derived from linear-regression rates using non-storm, 19th and 20th century data produce the lowest prediction error and uncertainty in the long-term trend.

ADDITIONAL INDEX WORDS: *Shoreline change, erosion rate, coastal storms, end-point rate, linear-regression rate, error in prediction, hindcast.*

INTRODUCTION

Over the past 40 years, coastal populations have swelled as a result of the convergence of a number of factors. Among these are a general increase in population from the post-WWII baby boom, a more affluent society, and the development of an infrastructure capable of transporting and supporting greater densities of coastal inhabitants and construction. In conjunction with a relative dearth of hurricanes and nor'easters since the 1960's (particularly on the U.S. east coast), these factors have led to burgeoning near-shore development.

In recognition of the hazards of living on the coast, many coastal states have begun to manage and sometimes restrict development in areas of erosion hazard. In addition, nearly all coastal states have, at a minimum, undertaken efforts to calculate long-term rates of erosion and use these data (often in map format) to control development through land-use management. Increased awareness of the detrimental impacts of coastal hazards spurred Congress in 1994 to pass legislation requiring the Federal Emergency Management Agency (FEMA) to conduct a study to determine whether the agency should map coastal erosion hazard areas and use these data in the implementation of the National Flood Insurance Program (NFIP) (CROWELL *et al.*, 1999b). The study was completed in early 2000, and is currently under Congressional review.

The increase in coastal development has stimulated study of the impact of storms on coastal structures, and has led to improved federal and state building codes and regulations. Houses constructed in conformance with performance standards put forth in the NFIP and local floodplain management ordinances and building codes are generally faring well in severe storms (MAHONEY, 1990; FEMA, 1997, 1999). Although the useful lifetimes of these larger, stronger structures have increased, they are surviving only to become threatened by the effects of long-term erosion. Shoreline retreat is a widespread problem; 80–90% of non-engineered shorelines along

99080 received 10 September 1999; accepted in revision 12 September 2000.

Table 1. *Abbreviations used in the manuscript.*

EP	End point
LR	Linear regression
TS	Temporal span
PI	Prediction interval
EIP	Error in prediction
CI	Confidence interval
RMS	Root mean square

the U.S. Atlantic coast are experiencing net erosion to some degree (GALGANO, 1998).

Accurate forecasts of coastal erosion, therefore, are critical to coastal managers and others charged with protecting the significant public investment at the coast. Analyses to determine shoreline-change rates at discrete intervals along the coast form the core of these forecasts. Considerable heterogeneity in the methods of data compilation and analysis, from the data used to the rate-calculation technique, exists among the coastal and Great Lakes states (CROWELL *et al.,* 1999a). While the variability in coastal morphology and presence of engineered shore-protection projects warrant some of these differences, few studies have quantified the typical prediction error associated with each method.

Calculation of Shoreline-Change Rates

Shoreline-change rates are calculated by monitoring the location of a representative shoreline indicator (*e.g.,* wet-dry line, berm crest, mean high water line, bluff line) over time. Shoreline-change maps are generated by compiling historical shoreline data (*e.g.,* NOS T-sheets, aerial photos) and recent surveys, incorporating the data into a digital medium, and correcting data for datum changes, distortion, or other errors (for a more detailed description of this process, see ANDERS and BYRNES, 1991; CROWELL *et al.,* 1991). Shoreline-change rates are typically calculated from these maps by plotting a line perpendicular to the numerous shorelines and measuring the amount of movement over time, which is defined by the dates of the plotted shorelines. Since the general trend in the U.S is long-term shoreline retreat, including the areas evaluated in this study, the convention for the remainder of the paper will be to refer to shoreline-change rates as 'erosion rates.' In those areas or time intervals characterized by accretion rather than retreat, the erosion rates will be negative.

Generally, two methods are used to calculate erosion rates: end point and linear regression. In end-point (EP; see Table 1) rate calculations, the total horizontal change between two shorelines (usually the oldest and the most recent) is measured. This distance is then divided by the number of years elapsed between the shoreline-position measurements, the temporal span (TS). With linear regression (LR), a best-fitting straight line is determined that minimizes the sum of squares of the differences between the measured and calculated shoreline positions. All shoreline positions can be used in the calculation of the best-fit line.

Other approaches relying on higher order functions, such as the Minimum Description Length (MDL) of FENSTER *et al.* (1993), have also been used to model shoreline change. CROWELL *et al.* (1997) applied this model to sea-level data used as a surrogate to demonstrate that simple linear regression provided results equal to or better than the MDL technique. Higher order methods may be appropriate to use in areas where non-linear coastal processes dominate, such as along southeastern U.S. barrier islands affected by cyclical tidal-inlet migration, but highly inaccurate results are possible.

Data Included in Shoreline-Change Analyses

Approaches differ on the issue of whether to use all available data to calculate erosion rates or selectively remove a subset of the data based on *a priori* knowledge of some factor affecting data quality. As mentioned previously, the use of EP rates automatically excludes most shoreline-position data, and has been shown to produce highly variable predictions depending upon which points are used (GALGANO *et al.*, 1998). With linear regression, all or most of the data points can be used, potentially reducing the impact of one or two anomalous values on forecast accuracy.

Shoreline-change data sets often include widely divergent shorelines mapped following the occurrence of great storms. Some argue that storms are a natural component of shoreline retreat, and as such, those mapped positions should be used in erosion-rate analyses (FENSTER and DOLAN, 1994, 1999). Other research suggests that natural post-storm recovery of the beach during the subsequent decade may even negate the effects of the storm, returning the shoreline to the position it would have occupied had the storm never taken place (MORTON *et al.*, 1994; GALGANO, 1998). Further, inclusion of storm-specific shorelines may add uncertainty and a negative bias to forecasts (GALGANO *et al.*, 1998; DOUGLAS *et al.,* 1998; DOUGLAS and CROWELL, 2000).

In addition to questions surrounding the role of storm-specific shorelines, the use of historical positions measured in the 19^{th} century has also come under question. The primary sources of these historical data are NOS T-sheets, which have 1-sigma measurement uncertainty of approximately 9 m (root mean square error) (CROWELL *et al.*, 1991). Despite this level of accuracy, there have been efforts made to de-emphasize the historical data in erosion-rate analyses (DOLAN *et al.*, 1991; FENSTER *et al.*, 1993). Although the prediction error associated with long-term versus short-term data has not been characterized fully, several studies have shown that the longer the temporal span of the data, the lower the uncertainty of the long-term trend (TANNER, 1978; GALGANO and LEATHERMAN, 1991; CROWELL *et al.*, 1993, 1997; BYRNES and HILAND, 1995).

Natural Variability in Shoreline Position

In addition to secular shoreline recession associated with increasing sea level, non-linear changes in shoreline position can occur over monthly, seasonal, and interannual timescales. In Delaware, the position of the HWL can vary by roughly 5–20 m between winter and summer months (BOSMA and DALRYMPLE, 1997). Similarly, regions along the south shore of Long Island experience seasonal changes on the order of 20 m (SMITH and ZARILLO, 1990). Decadal-scale variability on Long Island is thought to be related to wave focusing by shoreface sand ridges, interaction of the sand ridges

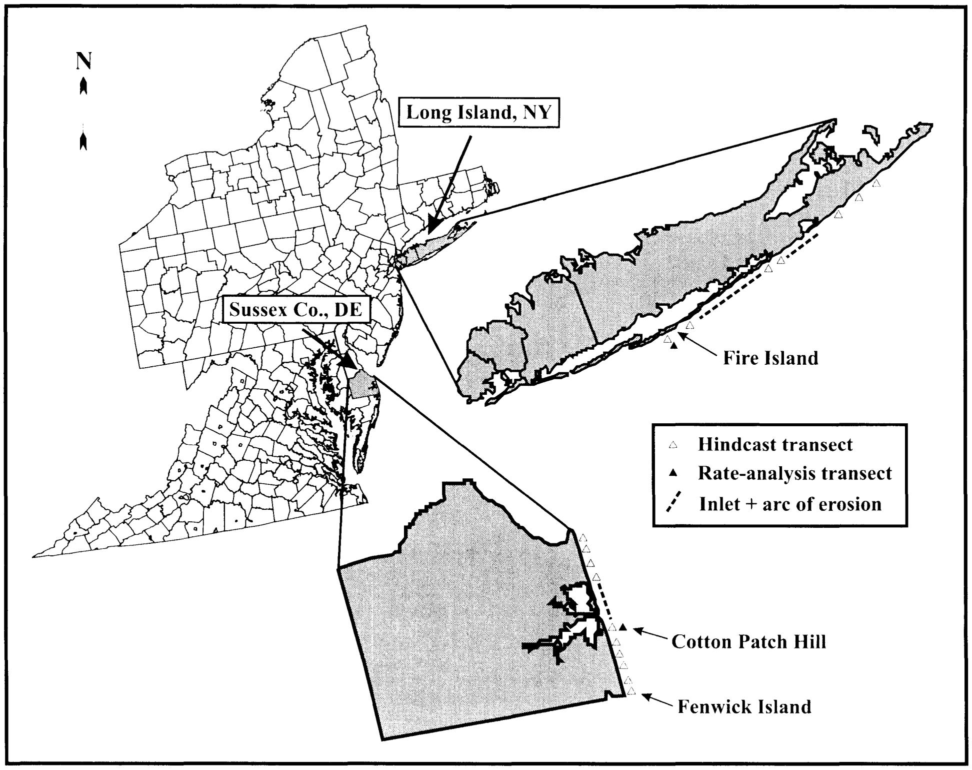

Figure 1. Study area.

with the nearshore bar, and/or onshore sediment transport from the ridges (SCHWAB *et al.,* 1999). In order to minimize the impact of seasonal and monthly variability, a common practice is to conduct surveys of the HWL following a neap high tide in late summer.

Clearly, the positions recorded in the shoreline database used in this study reflect individual snapshots in time, where the shoreline represents the cumulative impacts of sediment-transport processes operating over a variety of time scales. As discussed previously, some of the shorelines reflect immediate post-storm conditions, which can be verified independently with tide-gauge data or damage reports. The remaining shorelines are not storm-specific, but they are influenced by other processes that are difficult to quantify or remove completely. For the purposes of this paper, we ignore the implications of these residual processes; our analysis is intended to demonstrate patterns in prediction error associated with rate-calculation techniques and use of storm-specific shorelines.

Purpose of the Study

In this study, we use real shoreline data from Delaware and New York to address several unresolved issues concerning erosion-rate analyses. Specifically, we examine error in forecasts of future shoreline positions, looking for trends associated with the use of:

- EP versus LR rate-calculation methods;
- Storm-specific shorelines in the rate calculation; and
- Varying temporal spans of input data for calculation of erosion rates.

METHODS

Historical shoreline data from Delaware and the south shore of Long Island, New York, were obtained from a database compiled by Dr. Stephen LEATHERMAN of Florida International University (Figure 1). This database contains multiple shorelines depicting positions of the high water line, digitized from NOS (and predecessor-agency) T-sheets, orthophotos, aerial photographs, and GPS surveys. To minimize random profile variability, a common practice is to average shoreline positions for a portion of the coastline (FOSTER and SAVAGE, 1989), typically for distances on the order of hundreds of meters. For each state, positions along a 500-m segment of the shoreline were averaged to create a composite, shore-perpendicular transect, which was then used for detailed analysis. Care was taken to avoid selecting data from areas influenced by hard shoreline-protection structures, inlets, and other dynamic features (*e.g.,* prograding spits). For example, data from within the mapped arcs of erosion for Shinnecock (NY), Moriches (NY), and Indian River (DE) inlets (GALGANO, 1998) were avoided (Figure 1).

All possible combinations of shoreline positions in each transect were taken to calculate erosion rates using both EP and LR methods (Figure 2). The number of years elapsed be-

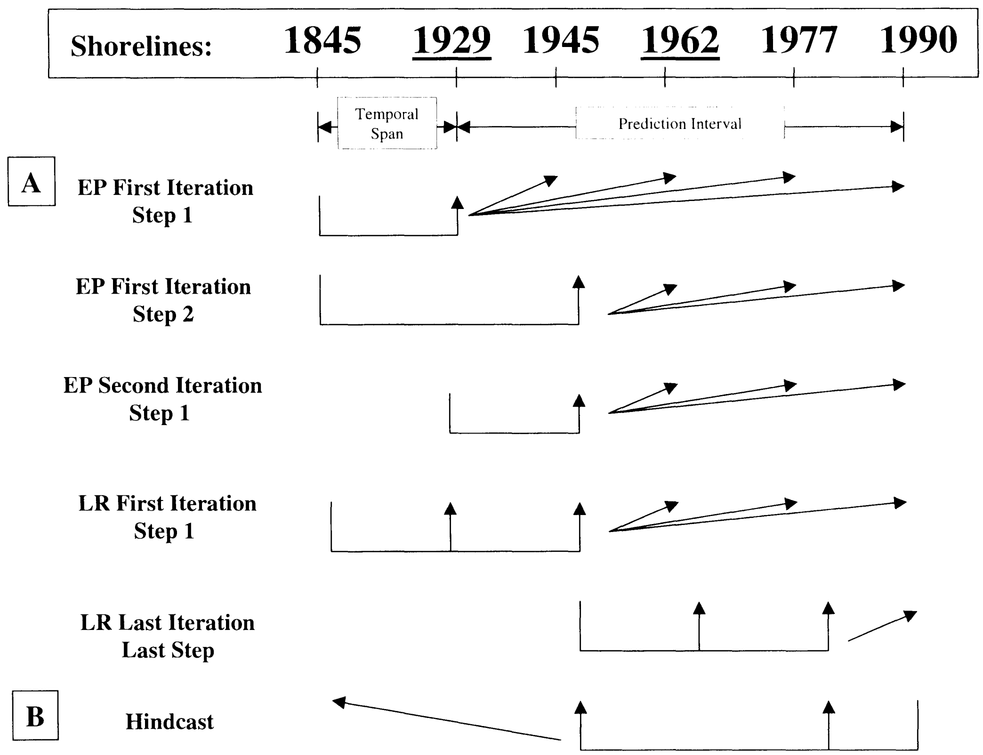

Figure 2. Experimental design. The dates for known shoreline positions are listed, with storm-specific shorelines underlined. (A) In the first iteration of the EP-rate calculation, the shoreline change between the first two positions (1845 and 1929) is calculated, with the Temporal Span calculated from the number of years elapsed between measurements (here: 84). With that rate, predictions are made to all subsequent positions, with the Prediction Interval representing the time elapsed between the predicted year and the last date from the rate calculation (arrows). In the second step, only the ending year for each successive EP-rate calculation changes. The start year is shifted up one position for the second iteration, and so on. For LR rates, three or more sequential positions are used, continuing through several steps and iterations. At least one position is withheld to serve as a prediction point. (B) To hindcast, the oldest shoreline position is predicted using a LR rate calculated from all 20th century, non-storm positions.

tween the oldest and most recent shorelines used to calculate the rate is referred to as the temporal span (TS) of the data (Figure 2a). Once the erosion rates for each temporal span were calculated, they were used to predict subsequent known positions (Figure 2a). The difference between the date of the last shoreline used in the rate calculation and the predicted year is termed the prediction interval (PI). The erosion rate is multiplied by the PI, and this predicted change in shoreline position is subtracted from the actual amount of change. The difference is called the Error in Prediction (EIP), and was determined for each erosion rate and concomitant predictions of subsequent shoreline positions.

For both EP and LR rates, separate calculations were made using the entire dataset of shoreline positions, and for a subset consisting of only non-storm shorelines. Designation of a "storm-specific shoreline" was based on *a priori* knowledge that a significant storm had occurred within a few months to a year or two of the measurement, which is in turn based on historical accounts of damage and evidence of multi-year recovery. Tide-gauge data showing extreme water elevations (two standard deviations above the tidal mean) were also used as independent verification of storm conditions (ZHANG, 1998).

In addition to forecasting later shoreline positions, we used a similar approach to hindcast 19th century positions (Figure 2b). All 20th century, non-storm data were used to calculate a LR rate, which was then used to predict the position of the 1870 shoreline in New York, or the 1845 or 1850 shoreline in Delaware. The intent was to test the reliability of these older data for erosion-rate analyses; are those positions consistent with the shoreline-change trends that we observe in the 20th century?

RESULTS

19th Century Data

Before assessing the error in forecasts of future shoreline changes, results from the hindcasting analysis provide information on the degree to which the 19th century data are consistent with the recent shoreline positions. The hindcast for the Cotton Patch Hill, Delaware, transect is shown in Figure 3(a). The predicted 1845 position is, for all intents and purposes, the same as the actual position, suggesting a high degree of reliability for the older data. Although the predicted position also falls within the 95% confidence interval (CI) of the data used in the rate calculation, the width of the CI at this location is nearly 200 m. (For a discussion of how the

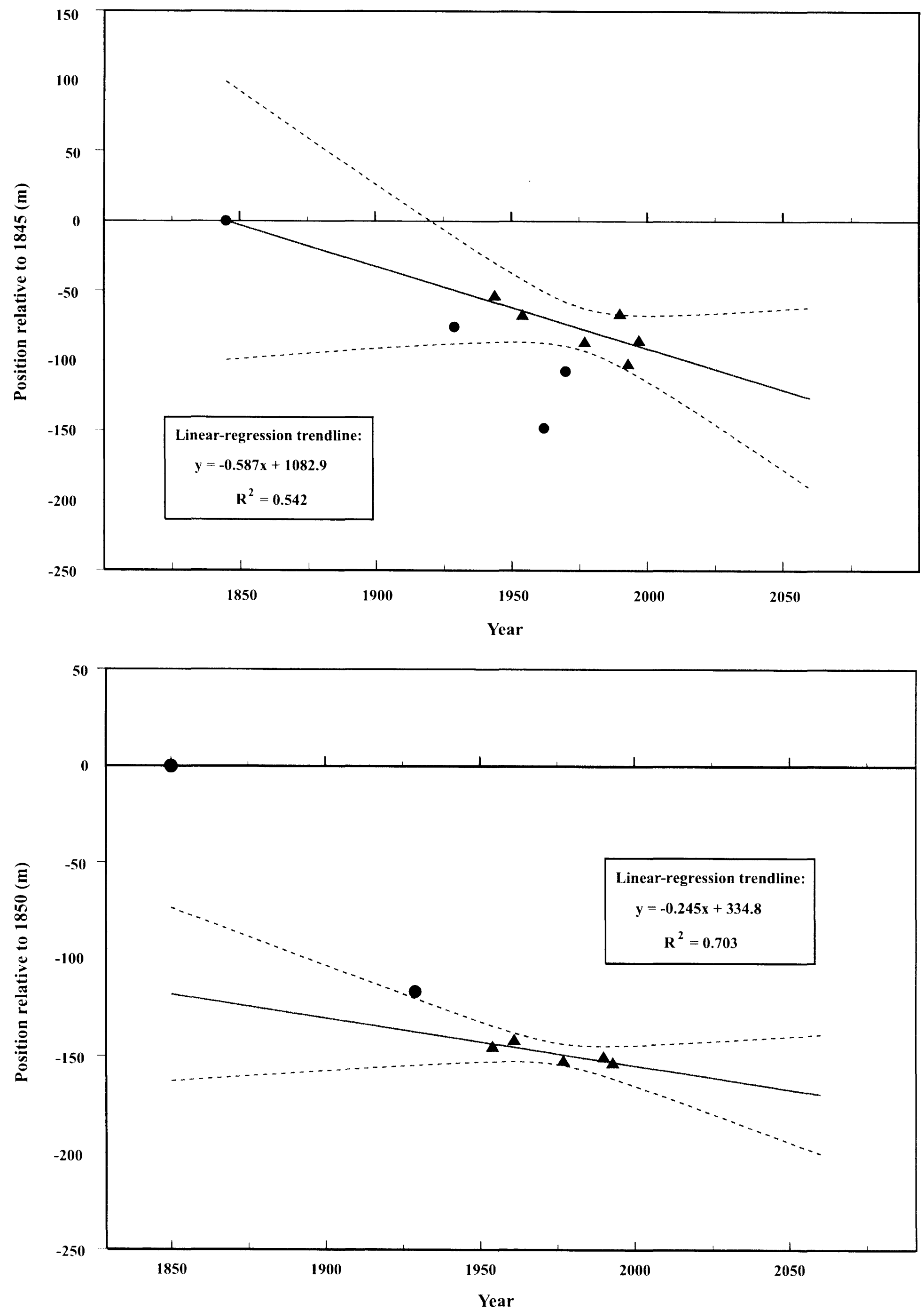

Figure 3. (a): Shoreline positions and hindcast, Cotton Patch Hill, Delaware. (b): Shoreline positions and hindcast, Fenwick Island, Delaware. Triangles mark shoreline positions (relative to 1845 or 1850) used in the calculation of the LR rate (LR trendline shown as solid line). Filled circles are positions excluded from LR rate, namely storm-specific shorelines (1929, 1962, 1970) and the 19th century position (1845 or 1850). Dashed lines are the 95% CI for the data.

95% CI is determined and how it may be used in erosion-rate analyses, see DOUGLAS and CROWELL, 2000). Nine additional transects from Delaware and seven from Long Island were tested to determine whether the initial results presented above are representative of the region as a whole (Table 2).

Although there is considerable variability in the prediction error on Long Island (both under- and over-shooting the 1870 position), all of the hindcasts fell within the 95% CI, and a few predictions were within 30 m of the actual shoreline position. Transect 5, where the CI is more than 700 m, was

Table 2. *Hindcasting results for New York and Delaware transects. For each transect, the Error in Prediction (EIP, in meters) is shown, as is whether or not the predicted 19th century position fell within the 95% CI. Width of the CI at the 19th century position is listed, calculated from the 20th century, non-storm positions and resulting LR rate.*

Transect	EIP (m)	Within CI?	CI Width (m)
New York			
1	13.0 m	y	452.6
2	21.5	y	332.5
3	27.9	y	1319.9
4	−48.5	y	145.9
5	−254.8	y	716.8
6	−58.8	y	157.2
7	44.7	y	219.4
Mean	−36.4		477.8
Delaware			
1	−48.0	y	185.4
2	61.4	n	120.3
3	−115.2	n	94.7
4	−72.9	y	180.3
5	−0.03	y	198.5
6	−118.3	n	176.5
7	−64.4	y	134.8
8	−51.5	y	236.8
9	−24.9	y	140.4
10	−117.9	n	89.6
Mean	−55.2		155.7

located updrift of the Moriches Inlet jetty, along Westhampton Beach. The large error may be related to the proximity of this transect to the jetty; the beach appears to be accretional over the last 60 years. The limited number of shorelines available along some stretches of Long Island reduced the quantity of data for the rate calculation (1 to 3 degrees of freedom), often resulting in confidence intervals considerably wider than the actual beach (*e.g.,* Transect 3). The averaged transect used in subsequent portions of the study was located near the southwestern end of Fire Island, where the most data are available.

In Delaware, the hindcasts also had highly variable values for the EIP, although most tended to undershoot the 19th century position. Width of the 95% CI was narrower and more consistent than what was observed in Long Island, owing to the three to five degrees of freedom for the LR-rate calculation (more 20th century, non-storm shorelines present in the Delaware dataset). The four hindcasts that failed to fall within the 95% CI were all composed of late 20th century data showing a minimal erosion trend (Figure 3b). Although none of these profiles are located adjacent to hard shoreline-protection structures, they are all adjacent to heavily developed coastal communities, some of which have histories of beach nourishment. The six profiles passing the hindcast test were located along undeveloped segments of the coastline (*e.g.,* state parks). Because the first transect presented in this section reflects the behavior of a natural shoreline and suggests high reliability of the 19th century position, it was considered a sufficiently representative transect and used in the remainder of the study.

Forward Predictions

Utilizing one averaged transect each from Delaware and New York, all possible combinations of shoreline positions were used to calculate erosion rates, with predictions made to all subsequent shorelines. The analysis was conducted on all shoreline data, and then again on a subset consisting of only non-storm shorelines. The EIP was calculated for each forecast, and the results are presented in Table 3.

The mean EIP is the arithmetic mean of all EIP values, positive or negative. A non-zero value indicates a tendency to systematically overestimate (−) or underestimate (+) erosion. In all but two sets of predictions (Delaware, LR), erosion was underestimated to varying degrees (Table 3). The mean of the absolute value for EIP was also calculated in order to determine the average *magnitude* of the error, regardless of which direction the forecast erred. The root mean square (RMS) average was also determined to show the magnitude of error for a majority of the predictions (*i.e.,* two-thirds of the absolute EIP values were at or below the RMS value).

End-Point and Linear-Regression Rates

The results in Table 3 show the overall decrease in prediction error when linear-regression rates are used in lieu of end-point rates. Focusing on the mean absolute EIP, predic-

Table 3. *Average prediction error for New York and Delaware shoreline data. All possible combinations of shoreline positions were used to calculate erosion rates and make predictions. Both end-point and linear-regression methods (minimum of three or four data points) were used, with and without known storm-specific shorelines. In the linear-regression sections, the number of predictions generated is listed (e.g., n = 20). The Error in Prediction (EIP) was calculated by subtracting the predicted position from the actual; therefore, a positive EIP indicates that more erosion actually occurred than was predicted. Mean EIP represents average error of all EIP values, positive or negative. Mean absolute EIP is the average of the absolute value of the error. RMS of absolute error was also calculated for comparison with the mean absolute EIP; two-thirds of the EIP values are below the RMS value.*

	End Point (m)			Linear Regression (m) (3 or more points)			Linear Regression (m) (4 or more points)		
	Mean EIP	Mean Absolute EIP	RMS Absolute EIP	Mean EIP	Mean Absolute EIP	RMS Absolute EIP	Mean EIP	Mean Absolute EIP	RMS Absolute EIP
New York									
storm	94.6	128.1	236.2	16.2 (n = 80)	35.4	53.7	17.3 (n = 55)	26.3	38.4
non-storm	9.8	17.8	21.7	3.2 (n = 20)	12.3	14.2	0.1 (n = 10)	9.3	10.1
Delaware									
storm	27.8	74.3	102.1	21.8 (n = 83)	48.9	64.1	23.8 (n = 56)	39.9	49.7
non-storm	0.2	19.2	23.2	−1.4 (n = 20)	18.5	20.9	−1.7 (n = 10)	20.4	22.2

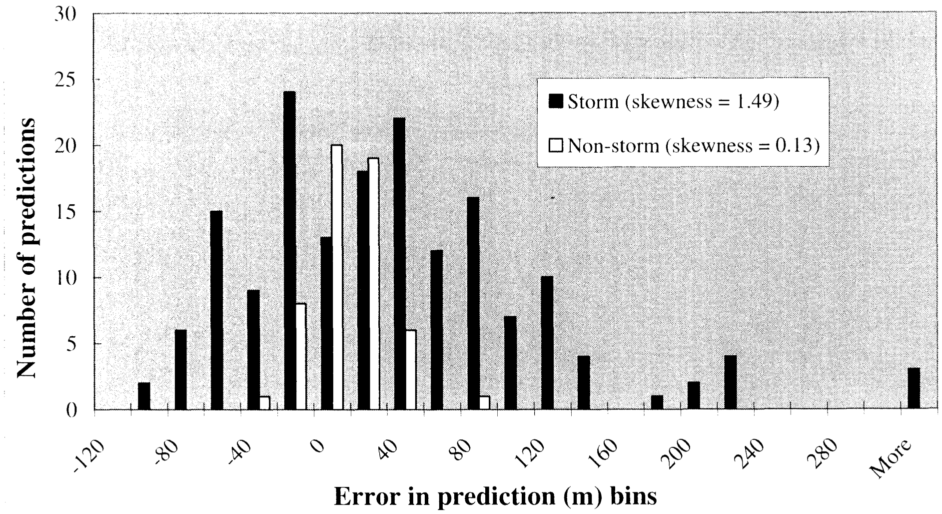

Figure 4. Storm and non-storm prediction error in Delaware. Histograms show the number of predictions where the EIP fell within the specified 20-m range of values. The skewness, the degree to which data vary from a normal distribution (represented by a value of zero), is shown for the storm and non-storm predictions. Those predictions exceeding the specified ranges (positive EIP only) are grouped together in the "More" category.

tion error in New York decreased by 72% for the storm-shoreline dataset when LR rates with a minimum of three data points were used, and by 79% when at least four shorelines were used. The reduction in error for non-storm data was 31% and 48% for minimum-of-3- and 4-point LR rates, respectively. In Delaware, the error decrease between EP and LR rates for storm data was 34% and 46% (3- and 4-point rates, respectively), but the trends for non-storm data are not as clear. While the error decreased by 4% from EP to 3-point LR rates, there was a 6% increase when the minimum-of-4-point-LR rates were used. These findings alone indicate that the rate-calculation methods are roughly equivalent for these specific data, however the limited number of predictions possible using linear regression ($n = 10$) may be an important factor.

Use of Storm-Specific Shorelines

As evident from the data in Table 3, removing storm shorelines from the analysis reduced the EIP considerably in both states, regardless of the rate-calculation method. In terms of the mean absolute EIP, the forecast error for LR data in New York was reduced to approximately 10 m, approaching the known accuracy of the data. In Delaware, the decrease in error is also considerable. However, as noted previously, the error is reduced by a factor of two or three to approximately 20 m for LR predictions, roughly twice the known accuracy. Clearly, the inclusion of storm-specific shorelines introduces a high amount of variability, and thus uncertainty, into erosion forecasts, but it is not the only contributing factor.

Another way of visualizing these results is presented in Figures 4 and 5. All EIP values for EP and LR predictions were combined *(in other words, the minimum number of shorelines for LR is reduced to two to include EP rates),* but still categorized as either storm or non-storm predictions. The range of the error for storm data is wide, from −100 m to over 200 m in both states. While there is a significant cluster of predictions with low EIP values, indicative of good erosion forecasts, there is also a large peak near +40 m in Delaware and at +80–100 m in New York, indicative of relatively poor forecasts. In contrast to the storm data, which appear to have a weakly bimodal distribution, the non-storm data have a nearly normal distribution in both states. The skewness of a dataset characterizes the degree of asymmetry of a distribution around its mean. In other words, the closer the value to zero, the closer the data approximates a normal distribution. Skewness values were calculated for both datasets in each state, and are also shown in Figures 4 and 5. The qualitative assessment that non-storm data have a more normal distribution is supported by the lower skewness values.

DISCUSSION

Caveats on the Forecast Error Estimates

Raw values were presented for the calculated error in erosion forecasts based on real shoreline-position data. Attempts were made to normalize the EIP to some time factor, such as TS or PI associated with each prediction. While there were trends showing a negative correlation between increasing TS and absolute error, and a positive correlation between increasing PI and absolute error, the variables were not separable; by virtue of the limited dataset, long TS almost always necessitated short PI, and vice versa. Because of these issues, and the suitability of confidence intervals and other statistical tools for showing uncertainty within a dataset, we elected to present the results in terms of the straight forecast error.

Average values for the forecast error are somewhat inflated as a result of our experimental design. The averaged transects from Delaware and New York each contain ten shoreline positions, three of which are known storm-specific shore-

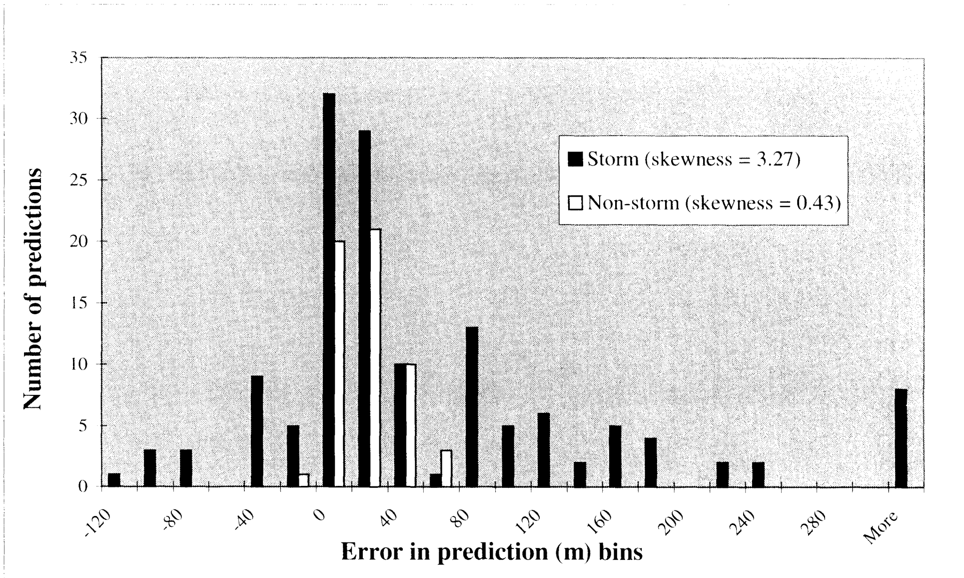

Figure 5. Storm and non-storm prediction error in New York. Refer to Figure 4 for explanation.

lines. At least one shoreline position had to be withheld from the rate calculations in order to have a position to predict to. When considering the non-storm data, only six of the seven existing positions could be used to calculate the erosion rate. Forecasts for management or other purposes, which are likely to use all non-storm data to calculate the LR trend, will almost certainly be better; the results presented here can be considered conservative error estimates. Conversely, in areas where fewer shoreline positions are available, the error estimates and forecast uncertainty (in the form of confidence intervals) are likely to be higher than the results presented here.

Rate-Calculation Methodology and Storm Impacts

In agreement with the results obtained by CROWELL *et al.* (1997) and GALGANO *et al.* (1998), linear regression was found to produce superior predictions over end-point rates. The trend is clear despite the limited number of possible predictions made with LR compared with EP. Given a larger dataset, or some weighting of the averages to the number of predictions, we would expect the decrease in error between the methods to be even more pronounced. The lack of a significant decrease in error in Delaware for the non-storm data likely reflects this data limitation. However, another important factor for non-storm data is that EP rates encompassing the longest possible TS yield fairly good predictions (CROWELL *et al.*, 1993, 1997), an effect observed in our analysis.

Our results show that while there is some reduction in error attributable to the use of LR rates, the most important factor in improving erosion forecasts is the exclusion of storm-specific shorelines. In New York, the best results were found not just with LR rates, but LR rates based on non-storm data.

Why does the use of storm-specific shorelines lead to such poor forecasts? GALGANO *et al.* (1998) demonstrated that arbitrary use of storm shorelines in calculating end-point rates results in extremely poor predictions of shoreline change. Linear regression, shown here to provide better forecasts, assumes that the process being modeled behaves in a linear fashion. Long-term erosion has been linked with the secular trend of sea-level rise on the U.S. Atlantic coast (ZHANG, 1998; LEATHERMAN *et al.*, 2000), which would indicate that this process could be a large component of the behavior observed here. Long-term change is precisely the type of behavior we seek to model, and it is this behavior that is of critical importance for numerous coastal management tools (*e.g.*, construction setbacks).

As mentioned previously, shoreline change also exhibits quasi-periodic variations on seasonal or interannual scales (*e.g.*, migration of tidal inlets or shoreface sand bodies), all of which are reflected to some degree in each measurement of shoreline position. Inspection of the confidence-interval results from Long Island (Table 2) shows widths two to three times greater than those calculated for Delaware even when 19^{th} century data are included, reflecting residual variance in the recorded shoreline positions. These results, in light of current research investigating the influence of antecedent geology and shoreface sand-supply on coastal evolution (SCHWAB *et al.*, 1999), suggest that non-linear components are likely to be critical factors controlling short-term shoreline change on Long Island. Over the long-term (> 60–100 yr), we expect that the linear component attributable to sea-level rise should increase in importance sufficiently to be reflected in the shoreline-change analyses.

After secular and quasi-periodic processes mentioned above, great storms are the third component of our model of shoreline change, and their infrequent, unpredictable nature cannot be adequately described by any type of linear equa-

Table 4. *Width of 95% confidence intervals, excluding and including 19th century data. First two columns show mean CI width at 19th century (1845 or 1850 in Delaware, 1870 in New York) or 21st century (2060) dates, based on LR analysis including only 20th century, non-storm shorelines. Values listed are the arithmetic mean of the CI widths for all transects listed in Table 2. Second pair of columns show CI width once the 19th century data are included in the LR trendline calculation.*

Transect	1845/50/70 CI (−19th cen.)	2060 CI (−19th cen.)	1845/50/70 CI (+19th cen.)	2060 CI (+19th cen.)
New York	477.8 m	431.5	175.7	224.2
Delaware	155.7	106.7	72.3	70.3

tion. Large-scale excursions of the shoreline from the long-term trend are valuable data for management purposes, potentially serving as a basis for additional setbacks beyond anticipated long-term erosion (DOUGLAS and CROWELL, 2000), analogous to the 'factor of safety' concept in engineering. However, the recovery of the shoreline to a position close to that predicted by a LR trend within a few years to a decade of the event (GALGANO, 1998), suggests that the storms are only important in describing short-term shoreline fluctuations. These positions reflect a different component of the model of shoreline change and, as demonstrated here and in DOUGLAS and CROWELL (2000), including them in the determination of the long-term trend can introduce large and unnecessary errors into erosion forecasts.

Importance of 19th Century Data

The hindcasting analysis revealed that 19th century positions are, for the most part, consistent with the trends observed in the 20th century. Exceptions to this observation were found in areas where there has been an apparent change in the magnitude of erosion, whether due to a history of beach nourishment or some other geologic or sediment-transport process (*e.g.*, antecedent geology, natural changes in sediment supply). In these instances, which given the pattern of coastal development could become the rule rather than the exception, there is some justification for not using the older data in erosion forecasts. However, the old positions would be critical for determining the long-term trend and the likely response of the shoreline should the erosion pattern change again (*i.e.*, beach nourishment ceases, a shoreline-protection structure is not maintained and fails, sediment supply changes, *etc.*).

Statistically, the 19th century data are essential for determining the uncertainty in erosion forecasts for the 21st century. As was seen in Table 2, the width of the 95% CI at the 1870 position in New York and the 1845 or 1850 position in Delaware was usually larger than the entire beach when only 20th century, non-storm data were used to calculate the erosion rate. Using the same data, the CI for the shoreline location in 2060 is approximately the same size (Table 4). If the 19th century positions are included in the analysis, we expect the width of the CI to decrease at that time interval. In addition, the CI for 2060 is also reduced considerably, down from 107 m to 70 m in Delaware, a 35% decrease in the possible location of the shoreline. This decrease in uncertainty includes CI widths from those transects where the 19th century positions were found to be inconsistent with the modern. Clearly, the old data are not only important in determining the long-term behavior of the shoreline in some cases, but are critical in helping to constrain estimates of shoreline location well into the future.

CONCLUSIONS

An analysis of real shoreline-position data from Delaware and New York has shown that inclusion of storm-specific shorelines drastically increases the error in forecasts of future positions. While there are certainly cases where end-point rates may yield good forecasts (*e.g.*, long temporal span, with storm shorelines omitted), linear-regression rates generally provide superior predictions. In the absence of major changes to sediment-transport processes during the period of measurement, 19th century shoreline positions were found to be accurate within the 95% CI of 20th century data and significantly decreased uncertainty in erosion forecasts.

Given the limited data available for determining shoreline-change trends and *a priori* knowledge of extreme events or other changes along the coast, the best erosion forecasts will be those derived from linear-regression rates using non-storm, 19th and 20th century data. Putting accurate information concerning the magnitude and direction of shoreline change (and the degree of uncertainty inherent to these forecasts) into the hands of coastal managers will grow in importance as development and redevelopment increases into the next century.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the helpful reviews of Drs. Robert Hallermeier, Robert Dean, and Mark Byrnes. This project was supported by FEMA contract EMW-1999-SA0244 (MGH), with additional support from NSF Graduate Research Traineeship Grant EHR94-53990 (to J. Sharp, Univ. of Delaware–College of Marine Studies, for MGH's dissertation research).

LITERATURE CITED

ANDERS, F.J. and BYRNES, M.R., 1991. Accuracy of shoreline change rates as determined from maps and aerial photographs. *Shore and Beach*, 59 (1), 17–26.

BOSMA, K.F. and DALRYMPLE, R.A., 1997. *Beach profile analysis along the Delaware Atlantic coastline.* University of Delaware, Center for Applied Coastal Research, Research Report No. CACR-97-05, 165 p.

BYRNES, M.R. and HILAND, M.W., 1995. Large-scale sediment transport patterns on the continental shelf and influence on shoreline response: St. Andrew Sound, Georgia to Nassau Sound, Florida, U.S.A. *Marine Geology,* 126, 628–655.

CROWELL, M.; DOUGLAS, B.C., and LEATHERMAN, S.P., 1997. On forecasting future U.S. shoreline positions: a test of algorithms. *Journal of Coastal Research,* 13 (4), 1245–1255.

CROWELL, M.; HONEYCUTT, M.G., and HATHEWAY, D., 1999a. Coastal erosion hazards study: phase one mapping. *Journal of Coastal Research,* Special Issue no. 28, 10–20.

CROWELL, M.; LEIKIN, H, and BUCKLEY, M.K., 1999b. Evaluation of coastal erosion hazards study: an overview. *Journal of Coastal Research,* Special Issue no. 28, 2–9.

CROWELL, M.; LEATHERMAN, S.P., and BUCKLEY, M.K., 1991. Historical shoreline change: error analysis and mapping accuracy, *Journal of Coastal Research,* 7 (3), 839–852.

CROWELL, M.; LEATHERMAN, S.P., and BUCKLEY, M.K., 1993. Shoreline-change rate analysis: long term versus short term data. *Shore and Beach,* 61, 13–20.

DOLAN, R.; FENSTER, M.S., and HOLME, S.J., 1991. Temporal analysis of shoreline recession and accretion. *Journal of Coastal Research,* 7 (3), 723–744.

DOUGLAS, B.C. and CROWELL, 2000. Long-term shoreline position prediction and error propagation. *Journal of Coastal Research,* 16 (1), 145–152.

DOUGLAS, B.C.; CROWELL, M., and LEATHERMAN, S.P., 1998. Considerations for shoreline position prediction. *Journal of Coastal Research,* 14 (3), 1025–1033.

FEDERAL EMERGENCY MANAGEMENT AGENCY, 1997. *Building Performance Assessment Report: Hurricane Fran in North Carolina—Observations, Recommendations, and Technical Guidance,* FEMA 290, 89 p.

FEDERAL EMERGENCY MANAGEMENT AGENCY, 1999. *Building Performance Assessment Report: Hurricane Georges in the Gulf Coast—Observations, Recommendations, and Technical Guidance,* FEMA 338, 110 p.

FENSTER, M. and DOLAN, R., 1994. Large scale reversals in shoreline trends along the U.S. Mid-Atlantic coast. *Geology,* 22, 543–546.

———, 1999. Mapping erosion hazard areas in the City of Virginia Beach. *Journal of Coastal Research,* Special Issue no. 28, 58–68.

FENSTER, M.; DOLAN, R., and ELDER, J.R., 1993. A new method for predicting shoreline positions from historical data. *Journal of Coastal Research,* 9 (1), 147–171.

FOSTER, P.E. and SAVAGE, R.J., 1989. Methods of historical shoreline analysis. *Coastal Zone '89,* New York: American Society of Civil Engineers, 4434–4448.

GALGANO, F.A., 1998. Geomorphic analysis of modes of shoreline behavior and the influence of tidal inlets on coastal configuration, U.S. East Coast. Ph.D. Dissertation, University of Maryland, College Park, Maryland, 332 p.

GALGANO, F.A.; DOUGLAS, B.C., and LEATHERMAN, S.P., 1998. Trends and variability of shoreline position. *Journal of Coastal Research,* Special Issue no. 26, 282–291.

GALGANO, F.A. and LEATHERMAN, S.P., 1991. Shoreline change analysis: a case study. *Coastal Sediments '91,* New York: American Society of Civil Engineers, 1043–1053.

LEATHERMAN, S.P.; ZHANG, K., and DOUGLAS, B.C., 2000. Sea-level rise shown to drive coastal erosion. *EOS, Transactions,* 81 (6), 55–57.

MAHONEY, M., 1990. The effects of coastal construction standards in reducing damages from Hurricane Hugo, *Proceedings of the Fourteenth Annual Conference of the Association of State Floodplain Managers,* ASFPM, 195–198.

MORTON, R.A.; PAINE, J.G., and GIBEAUT, J.C., 1994. Stages and durations of post-storm beach recovery, southeastern Texas coast, U.S.A. *Journal of Coastal Research,* 10 (4), 884–908.

SCHWAB, W.C.; THIELER, E.R.; ALLEN, J.S.; FOSTER, D.S.; SWIFT, B.A.; DENNY, J.F., and DANFORTH, W.W., 1999. Geologic mapping of the nearshore area offshore Fire Island, New York. *Coastal Sediments '99,* New York: American Society of Civil Engineers, 1552–1567.

SMITH, G.L. and ZARILLO, G.A., 1990. Calculating long-term shoreline recession rates using aerial photographic and beach profiling techniques. *Journal of Coastal Research,* 6 (1), 111–120.

TANNER, W.F., 1978. *Standards for Measuring Shoreline Change.* Department of Geology, Florida State University, Tallahassee, Florida, 87 p.

ZHANG, K., 1998. Twentieth Century Storm Activity and Sea Level Rise Along the U.S. East Coast and Their Impact on Shoreline Position. Ph.D. Dissertation, University of Maryland, College Park, Maryland, 266 p.