Journal of Coastal Research	17	3	714–720	West Palm Beach, Florida	Summer 2001

Coastal Storms and Shoreline Change: Signal or Noise?

Michael S. Fenster†, Robert Dolan‡, Robert A. Morton§

†Randolph-Macon College
Environmental Studies Program
Ashland, VA 23005, U.S.A.
mfenster@rmc.edu

‡University of Virginia
Department of Environmental Sciences
Charlottesville, VA 22903, U.S.A.
rd5q@virginia.edu

§U.S. Geological Survey
Center for Coastal Geology
St. Petersburg, FL 33701, U.S.A.
rmorton@usgs.gov

ABSTRACT

FENSTER, M.S.; DOLAN, R., and MORTON, R.A., 2001. Coastal Storms and Shoreline Change: Signal or Noise? *Journal of Coastal Research,* 17(3), 714–720. West Palm Beach (Florida), ISSN 0749-0208.

A linear regression (studentized) residual analysis was used to identify potential shoreline position outliers and to investigate the effect of the outliers on shoreline rate-of-change values for transects along the Outer Banks, North Carolina. Results from this analysis showed that, over a 134 year period, storm-influenced data contribute statistically significant information to the long-term signal. Consequently, storm-influenced data points do not appear to be temporal outliers and thus, do not need to be excluded from a long-term analysis of shoreline changes. Furthermore, projections of the upper and lower confidence intervals (CIs) for the regression line to the year 2010 (24 year extrapolation) showed that including or excluding outliers had minimal effects on shoreline position predictions.

ADDITIONAL INDEX WORDS: *coastal storms, shoreline rate-of-change, shoreline movement, statistical analysis, outliers.*

INTRODUCTION

In this paper we pose the questions, "When do tropical and extratropical cyclones cease to influence the long-term shoreline migration history of storm-influenced coasts?" In other words, "Do storm-influenced shorelines create outliers in shoreline change data sets that aperiodically bias the long-term shoreline trends or, conversely, do these data contribute information about long-term shoreline migration history?" Moreover, is it appropriate to eliminate storms from shoreline change data bases in an effort to increase the linearity of a trend as suggested by DOUGLAS and CROWELL (2000) and HONEYCUTT *et al.* (in press)? Or, perhaps, do these data points contribute information tō help describe a potentially non-linear system that is influenced by the frequency and magnitude of storms?

Geologists have long known that storms control shoreface retreat (SWIFT, 1968; LEATHERMAN *et al.*, 1977; BOYD and PENLAND, 1984), provide sand for storm washovers and flood-tide deltas (SWIFT, 1975; NIEDORODA *et al.*, 1985), and produce facies in the rock record indicative of storm-dominated coastal and shallow marine depositional environments (HAMBLIN and WALKER, 1979). At the other end of the temporal spectrum, coastal storms can substantially alter the shoreline position immediately after passage of the cyclone (DOLAN *et al.*, 1991), but it is unclear when a shoreline becomes a "post-storm" shoreline (*i.e.,* having completed "recovery"). Temporal scale is a central issue involved in addressing the questions posed above. It is well known that the time scale over which we observe processes and responses can influence our perceptions of system dynamics and our conclusions regarding cause and effect relationships within those systems (LEOPOLD *et al.*, 1964; SCHUMM and LICHTY, 1965; CHORLEY and KENNEDY, 1971; and SCHUMM, 1977). Moreover, AGAR (1980) and DOTT (1983) have raised questions regarding the role of average, continuous, day-to-day processes versus relatively rarer, large-magnitude processes in producing sedimentary rock sequences.

In order to understand better the role of aperiodic coastal storms in influencing shoreline change, we consider (1) what constitutes a temporal outlier in shoreline change analysis and (2) the basic types of errors associated with shoreline position data. The occurrence of outliers within data sets is one of the oldest and most persistent problems in data analysis. Outliers can be considered observations that were generated by mechanisms distinct from those of the family of observations. Results generated by mathematical maximization procedures, such as regression, discriminant analysis, and principal component analysis, are particularly sensitive to errant data and the use of such data can lead to incorrect results and faulty interpretations (*e.g.,* STEVENS, 1984).

Two main categories of outliers exist with respect to shoreline data; temporal and spatial (Figure 1). Temporal outliers include those shoreline position/time data points that appear to deviate markedly from other members of the sample used to compute a rate-of-change at one transect location. Outliers can be expected to differ greatly in magnitude (on y or in the space of the predictors) from the other observations (inliers) or from a statistical estimate (HAWKINS, 1990). In the temporal domain, outliers can bias or distort estimates of the long-term trend. Such outliers commonly result in regression sensitivity and/or wield undue influence on a regression

00066 received 16 May 2000; accepted 17 August 2000.

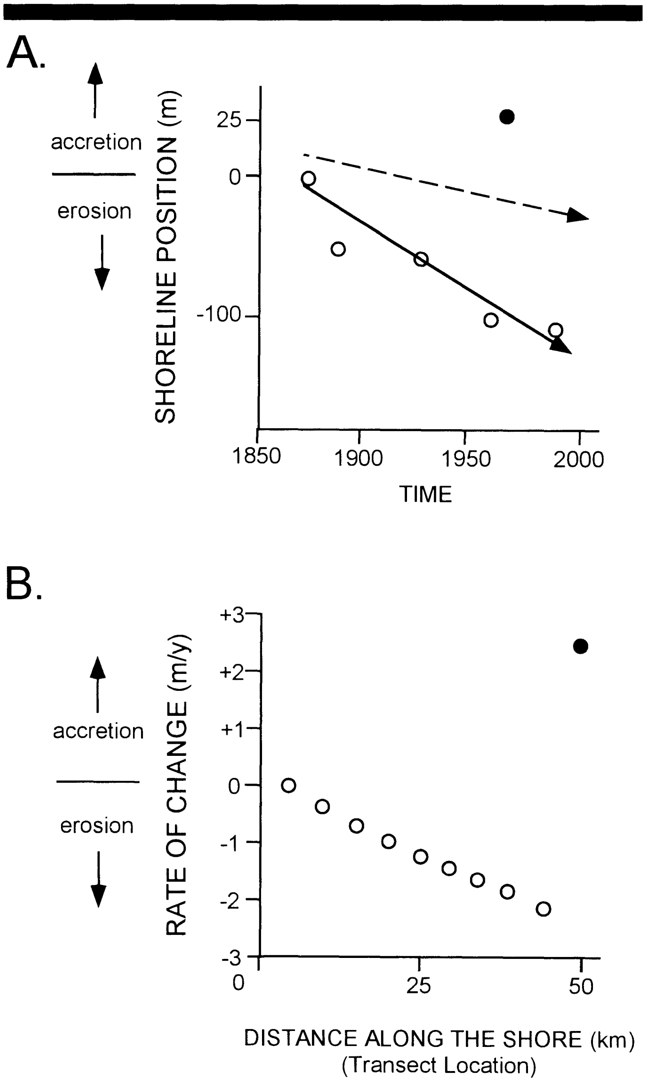

Figure 1. Two common types of outliers (black circles) in shoreline change data sets: (A) Temporal outliers in which a shoreline position is "signficantly" removed from other shoreline positions in time and (B) Spatial outliers in the shoreline rate-of-change values along the shore. The dashed line in (A) represents the regression line including the outlier and the solid line represents the regression line excluding the outlier.

equation (including the slope or rate-of-change). Spatial outliers are those which show unusually large or small rate-of-change values at individual transect locations along the shore. Common spatial outliers include shorelines influenced by tidal inlets (FENSTER and DOLAN, 1996) or anthropogenic activities (MORTON, 1979). The two main types of temporal outliers include coarse outliers and inherent outliers. Coarse outliers (a.k.a., measurement and execution errors) usually involve operator blunders and are generally large and irregular in occurrence. Sources of coarse or gross outliers include mistakes in data input, incorrect computations, misreading of data, or negligence. Inherent outliers can result from systematic sources which result in samples with unusually large or low values and are displaced in a constant direction. Sources include miscalibrated instruments, distortion in data (*e.g.*, aerial photographs), or processes, such as storm set up or set down, which move the shoreline consistently either landward or seaward (DOLAN and FENSTER, 1995). Additionally, inherent errors can result from the natural variability of a population. In this case, the data points may reflect the distributional properties of a correct model describing the data (*e.g.*, normal distribution). The outliers may simply represent data from the tails of this population.

Data outliers are not always obvious or easily detectable. In some cases, however, outliers can be readily detected or are intuitively obvious upon examination of the data. Various outlier detection methods have been designed to identify quantitatively and isolate the outliers (diagnostic methods for detection in *large* data sets) (*e.g.*, HAWKINS, 1980). Once detected, the decision to include or delete outliers from an analysis is not always straightforward. Two main approaches can be considered to deal with outliers: (1) remove the outliers and risk distorting reality; and (2) include the outliers which may reveal something essential about reality. If inclusion is desired, the type of outlier should determine the type of treatment necessary. In turn, the treatment selected commonly will be a function of how we view the outliers relative to the types of questions being asked. In addition, some robust methods can be used to make inferences using outliers, or the influence of an outlier can be reduced by weighting procedures.

Since regression analysis is often used to compute shoreline rates of change over periods ranging from decades to centuries, we ask the following questions:

(1) Can temporal outliers be detected in the relatively small sample shoreline position data sets that are used to compute shoreline rates of change at specific locations or transects?
(2) What are the physical processes responsible for producing outliers?
(3) Are there patterns in the distribution of outliers that can be used to assess large sets of shoreline data?
(4) Should we use or exclude the outliers from rate-of-change calculations?

For these analyses we use the null hypothesis that episodic, large magnitude meteorological forcing events, such as those associated with storms, do not directly control shoreline movement over the long-term. Rather, long-term shoreline changes occur as a result of the synergistic activity of day to day processes or through the influence of longer-term processes such as sea-level rise or fall (independently from storm-related processes) or changes in sediment supply. Under this hypothesis, storms tend to (1) displace the shoreline systematically landward or seaward from its pre-storm position and (2) to produce shoreline position/time data that deviate from the "true" long-term trend as estimated from a time series of measured shoreline positions. Following the storm, the shoreline returns to near its pre-storm position (DOUGLAS and CROWELL, 2000; HONEYCUTT *et al.*, in press). The alternate hypothesis envisages that non-storm, day to day and long-term processes, unrelated to storms, maintain shoreline position while storms control the long-term shore-

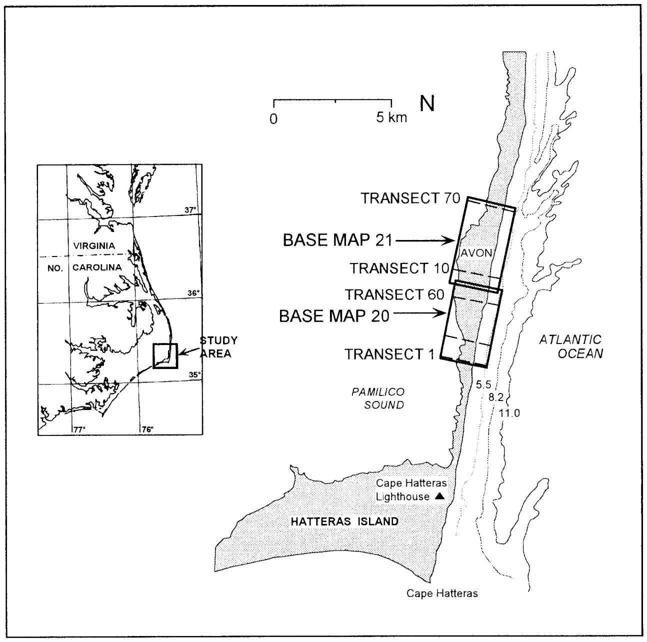

Figure 2. Map of the study area at Hatteras Island, North Carolina. Base maps 20 and 21 (rectangles) and examples of transects (dashed lines) are indicated on the map.

line trends. For this analysis, storm-influenced data points would not be detected as outliers. For the analyses presented here, storm-influenced data points are defined as those in which a storm with deep water wave heights $\geq$ 1.8 m had occurred less than two weeks prior to a photogrammetric flight.

METHODS

A linear regression (studentized) residual analysis was used to identify temporal outliers and to investigate the effect of the outliers on shoreline rate-of-change values. Once identified, we used the definition above to determine if the temporal outliers were storm- or non-storm-influenced. Furthermore, to establish what effect the inclusion or exclusion of outliers has on shoreline position predictions, we projected the upper and lower confidence intervals (CIs) for the regression line to the year 2010 and compared the predictions of the two scenarios (DOLAN and FENSTER, 1995).

Residuals and Outliers

With respect to linear regression techniques, residuals can be conceived of as the deviation of the data (observed) from the fitted (predicted) values, and are a measure of the variability not explained by the regression model (KLEINBAUM and KUPPER, 1978; MONTGOMERY and PECK, 1992). Residuals are defined as:

$$e_i = SP_i - \widehat{SP}_i, \quad i = 1, 2, 3 \ldots, n \qquad (1)$$

where SP_i is the ith shoreline position, and $\widehat{SP}_i$ is the corresponding fitted value.

Table 1. *Storm-influenced shoreline positions and corresponding dates. National Ocean Service historical maps are denoted by NOS T and aerial photographs by AP. Storms which occurred about a week prior to photogrammetric flights are indicated by date, duration, average wind speed and deep water wave height (H_0) (After* DOLAN *et al., 1991).*

Date	Type	Date of Prior Storm (max = one month)	Duration (hrs)	Ave. Wind Speed (kts)	H_0 (m)
1852	NOS T	NA			
1917	NOS T	NA			
01 Jul 45	AP	None			
10 Oct 58	AP	01-03 Oct 58	29	23	3.1
13 Mar 62	AP	07-08 Mar 62	44	44	9.1
13 Dec 62	AP	None			
03 Oct 68	AP	None			
04 Jun 74	AP	04 Jun 74	15	18	1.8
21 Oct 80	AP	None			
21 Aug 81	AP	None			
14 Jul 82	AP	None			
27 Oct 82	AP	22–26 Oct 82	64	37	7.2
26 Jan 83	AP	21–22 Jan 83	36	18	2.1
27 Apr 83	AP	24 Apr 83	9	26	2.6
20 Sep 84	AP	13–14 Sep 84*	24–48	20	2.4
18 Aug 86	AP	17 Aug 86	22	27	3.4
01 Oct 86	AP	None			

* Hindcast estimate from NOAA weather maps

Although a qualitative definition of an outlier is presented above, quantitative definitions of an outlier vary. For example, outliers can be considered extreme observations that are larger in absolute value than other residuals by three or more standard deviations from the mean (KLEINBAUM and KUPPER, 1978; MONTGOMERY and PECK, 1992). For this study, we used the more conservative standard deviation of $\pm$ 1.8 and $\pm$ 2.2 standard deviations, corresponding with a 90% and 95% confidence interval, respectively (compared to 99% for $\pm$ 3 standard deviations) in order to identify and produce a greater number of outliers. Outliers in this study are expected to be from a "heavy-tailed distribution" in which the shoreline positions in the "tails" of a population of shoreline positions are a function of extreme meteorological forcing, such as storm events, rather than from erroneous data due to faulty analysis or incorrect readings.

To ascertain whether the shoreline positions constitute extreme values, we calculated residuals from two base maps (20 and 21), each comprising 72 transects spaced at 50 m intervals, along the Outer Banks of North Carolina (DOLAN and FENSTER, 1995; Figure 2). The temporal data incorporated at least 13 shoreline position/time data points and spanned the period 1852 to October 1986 (Table 1). To avoid problems associated with spatial autocorrelation, we selected transects nearly 600 m apart (DOLAN *et al.*, 1992). This approach ensured that the shoreline position at each location in time is independent and identically distributed (DOLAN *et al.*, 1992). In order to compare and contrast the residuals from each transect directly, we calculated "studentized" residuals (MONTGOMERY and PECK, 1992):

$$r_i = \frac{e_i}{\sqrt{MSE\left[1 - \left(\dfrac{1}{n} + \dfrac{(x_i - \bar{x})^2}{\sum_i (x_i - \bar{x})^2}\right)\right]}} \qquad (2)$$

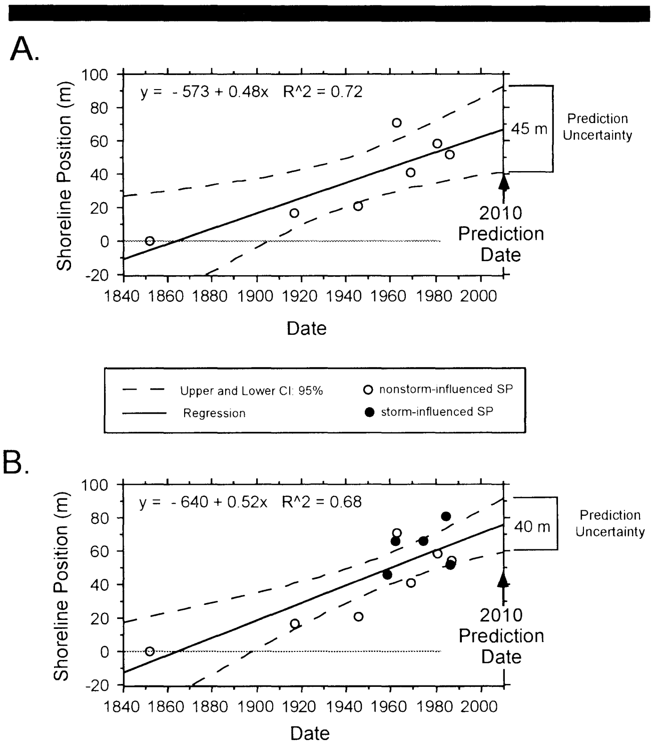

Figure 3. Plot of regression lines and confidence intervals for transect 21-13, Hatteras Island, without storm-influenced data (A) and with storm-influenced data (B). Note that the prediction uncertainty does not vary considerably between the two data sets.

where r_i is the ith studentized residual, n is the number of shoreline positions, x is the date of the ith observation, $\bar{x}$ is the mean date, and MSE is the mean squared error:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{SP}_i - \widehat{\mathrm{SP}}_i)^2. \qquad (3)$$

Studentized residuals are standardized (each e_i is divided by its estimated standard deviation) to produce a mean of 0 and a constant variance equal to one, regardless of the shoreline position relative to the location of x_i (in this case date). Comparing the studentized residuals to the t-statistic yields a level of confidence for outlier detection. Since studentized residuals were computed rather than residuals, and given that the population variance is unknown, the t-statistic was used to test the outliers for significance and to derive the critical region in which outliers exist at the 90% CI (*i.e.,* ± 1.8 standard deviations) and the 95% CI (*i.e.,* ± 2.2 standard deviations).

Confidence Intervals

In order to test the reliability of shoreline predictions excluding and including outliers, we fit a linear regression line on historical shoreline data from transect 21–13, both excluding (Figure 3A) and including (Figure 3B) storm-influenced data. We chose transect 21–13 because it was not influenced by secondary processes associated with capes, inlets, and rivers, or by anthropogenic factors such as groins and beach nourishment projects. Table 1 lists the hindcasted storm-influenced shoreline positions and corresponding dates. Furthermore, we extrapolated the regression lines to the year 2010 to test predictions using storm and non-storm data (DOLAN and FENSTER, 1995). Upper and lower CIs were calculated and projected to the year 2010 using:

$$\mathrm{C.I.} = \widehat{\mathrm{SP}}_i \pm (t_{n-2,\alpha/2})\sqrt{\mathrm{MSE}\left(\frac{1}{n} + \frac{(x_i - \bar{x})^2}{S_{xx}}\right)} \qquad (4)$$

where $t_{n-2,\alpha/2}$ is the t-statistic for n shoreline positions at a confidence level of $\alpha/2$ and S_{xx} is:

$$S_{xx} = \sum_{i=1}^{n}(x_i - \bar{x}_i)^2. \qquad (5)$$

The width of the CIs is a minimum for $x_0 = \bar{x}$, and widens as $|x_0 - \bar{x}|$ increases since the best estimates of Y (shoreline position) will be made at X values (date) near the center of the data; and the precision of the estimation is likely to decline towards the boundary of the x (time) (MONTGOMERY and PECK, 1992). This phenomenon suggests that the worst estimates of shoreline position will occur near the earliest and latest dates.

STUDY AREA

Hatteras Island, North Carolina was selected for study because it is impacted by both tropical and extra-tropical storms, and previous studies have yielded rich data-sets of hindcasted storm attributes and shoreline positions (Figure 2; DOLAN *et al.*, 1988; DOLAN *et al.*, 1991; DOLAN *et al.*, 1992; FENSTER *et al.*, 1993). Hatteras Island is part of an open-ocean, wave-dominated, long, linear barrier island system (HAYES, 1979; INMAN and DOLAN, 1989). Shoreline movement is dominated by longshore and cross-shore sediment transport resulting from wave action. The mean wave height is approximately 0.65 m, however, the wave climate is temporally and spatially variable (INMAN and DOLAN, 1989). Previous studies have shown that 25% of all winds are from the northeast, under the influence of (winter) Arctic and polar air masses (THOMPSON, 1977; JENSEN, 1983; LEFFLER *et al.*, 1990). The predominant summer wave approach is southerly, under the influence of tropical maritime air masses and cyclonic low pressure activity (FENSTER and DOLAN, 1993). Between 1942 and 1984, the area was subject to storms with winds capable of generating deep-water wave heights in excess of 1.6 m every ten days, on average; 3.4 m every three months; one of at least 5.2 m every three years; and one greater than 7 m every 25 years. In addition, the period of maximum storm frequency (51% of all storms) occurred between December and March, with an average of 4 storms per month (DOLAN *et al.*, 1988).

RESULTS

A histogram showing the distribution of the studentized residuals from all transects analyzed within base maps 20 and 21 of Hatteras Island is plotted in Figure 4. A summary of the statistically significant studentized residuals from these transects is provided in Table 2. Only 7 of 144 shoreline

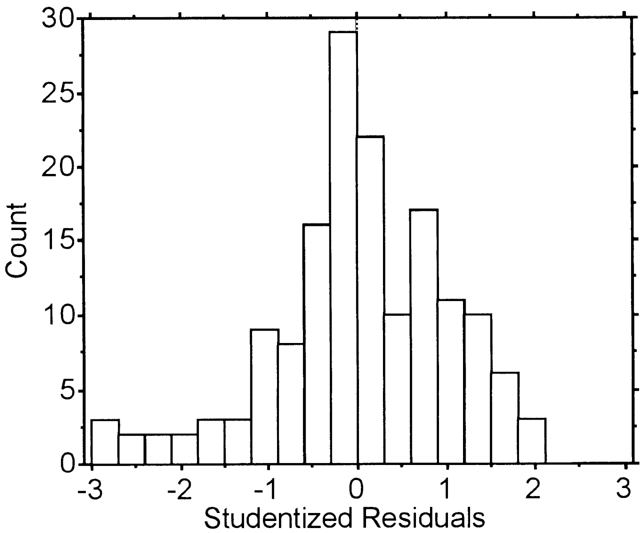

Figure 4. Histogram of studentized residuals from base maps 20 and 21, Hatteras Island. Note the relatively low number of extreme values.

positions (< 5%) were identified as potential outliers at the 95% CI. Three additional values were significant at the 90% CI (< 7%) (Table 2). Only one transect contained two outliers (20–49). Only two of the 10 identified outliers occurred over the period of photogrammetric data and the remaining outliers occurred over the period of map and chart data. Linking the individual outliers to the storm information clearly shows that storm-influenced data points are not outliers (compare Tables 1 and 2).

Figure 3 shows the regression lines and the 95% confidence bands for transect 20–13, projected to the year 2010. As stated quantitatively above, the curvature of the confidence bands indicate that the estimates are most precise at the average value of x ($\bar{x}$, date) and become less meaningful away from the average date. According to equation (4), the factors that cause the confidence band to increase in range include an increase in MSE, a minor increase with a reduction in the number of data points, n, a decrease in S_{xx}, and a data set with points located far from $\bar{x}$ (mean date).

The confidence bands shown in Figure 3 indicate that we can be 95% confident that the true estimate is located in this interval. Figure 3A does not include storm-influenced data points while Figure 3B includes all data points. Inclusion of the storm data decreases the uncertainty involved in predicting the shoreline's position for the year 2010 and does not significantly increase the variability of an estimate of future shoreline position. In addition, the R^2 value increased only slightly from 0.68 to 0.72 after excluding storm data (insignificant at the 95% confidence level). These results support the alternate hypothesis that storms influence or control the long-term shoreline trends.

DISCUSSION

Residual Analysis

The results presented in Table 2 suggest that storm-influenced data points are not outliers. Six of the seven data points significant at the 95% CI are 1917 map dates; the other value is a 1945 non-storm-influenced date. At the 90% CI, only 3 significant values were plotted in addition to those from the 95% CI: two map dates (1852 and 1917) and a 1945 non-storm-influenced date. The 1917 map date was the most persistent outlier. It cannot be confirmed whether this is a "process" related outlier because the shoreline position was mapped over an unspecified period of time, at an unknown date in that year. In addition, the shoreline shown on 1917 T-sheet may have been poorly (inaccurately) mapped in this area or the map may have been poorly produced when drafted by the National Ocean Service (NOS). The 1945 value is the only aerial photograph derived position depicted as a possible outlier; this position was not storm-influenced (Table 2). In addition, the 1945 residuals at the two transects (21–1 and 21–37), spaced about 1.8 km apart, lie on opposite sides of the regression line. This result indicates one position is landward of the estimate (21–1) while the other (21–37) is seaward of the estimate. This finding demonstrates the ability of the shoreline to show highly variable temporal trends over relatively short spatial regions or, once again, for the shoreline to have been mapped from poor quality data. Of particular importance to the study of outliers, and contrary to expectations for this wave-dominated coastline, is the result that storm-influenced data do not yield significant variability unaccounted for by the regression model.

Table 2. *Summary statistics of significant studentized residuals for transects 600m apart from base maps 20 and 21, Hatteras Island, North Carolina.*

Base Map-Transect	Outlier Date	Shoreline Position (m)	Studentized Residuals
20-1	1917	299	−1.812*
20-13	1917	305	−2.460**
20-25	1917	338	−2.205**
20-37	1917	345	−2.996**
20-49	1852	382	1.868*
20-49	1917	353	−2.535**
21-1	1945	320	−2.278**
21-37	1945	415	2.028*
21-49	1917	279	−2.906**
21-61	1917	200	−2.886**

* t-statistic significant at 90% CI for two-tailed test, 11 df (>1.796)
** t-statistic significant at 95% CI for two-tailed test, 11 df (>2.201)

Confidence Intervals

According to the null hypothesis presented above, which is similar to that presented by DOUGLAS and CROWELL (2000) and HONEYCUTT *et al.* (in press), the exclusion of storm-influenced data points reduces prediction variability. The results shown in Figure 3 indicate that the range of uncertainty for shoreline predictions is *greater* in cases *excluding* storm-influenced data (prediction uncertainty in shoreline position at 2010 = 45 m; Figure 3A) compared to cases including such data (prediction uncertainty in shoreline position at 2010 = 40 m; Figure 3B). Consequently, these data do not support our null hypothesis or those of DOUGLAS and CROWELL (2000) and HONEYCUTT *et al.* (in press). Additionally, the inability of storm-influenced data to bias shoreline forecasts is revealed by insignificant changes in the rates of shoreline change (Figure 3A = −0.48 m/yr; Figure 3B = −0.52 m/yr) and the R^2 values (Figure 3A = 0.72; Figure 3B = 0.68). These results suggest that the impact of an individual "powerful" storm (*e.g.,* the March 1962 storm) or the cumulative and synergistic effect of many (small and/or large) storms most likely influence the long-term shoreline migration history at this location (FENSTER and DOLAN, 1994). For example, in 1968, six years after the 1962 Ash Wednesday storm, the shoreline at this location along the Outer Banks moved seaward to its "original" 1958 (storm-influenced) position—only to return to the exact March 1962 shoreline position immediately following a relatively small magnitude 1974 storm (Table 1; Figure 3B).

Along this storm-influenced coast, shorelines move systematically landward under the influence of storm-related processes, but rarely have the opportunity to fully "recover" to a "pre-storm position." These data support the observations of DOUGLAS and CROWELL (2000) which show post-storm accretion continuing for a decade or more along the Delaware coast before "returning" to a storm-influenced erosional condition at a later date. The persistence of these short-term changes at a particular reach (*i.e.,* post-storm recovery) will depend on many factors including the duration and intensity of an individual storm and the frequency of successive storms. In this context, it is difficult to discern when storms cease to influence a coast because the erosion/accretion "cycles," which may persist for a decade(s), tend to control or influence shoreline migration. These data suggest that storms are not temporal outliers in shoreline change data sets but drive a relatively non-linear system. Finally, the results from the Outer Banks demonstrate the ability of the linear regression method to minimize the influence of extreme values or outliers—especially as compared to the end point rate method since adding more points (DOLAN *et al.*, 1991) and increasing the time span decreases uncertainty in rate-of-change estimates (DOLAN *et al.*, 1991; CROWELL *et al.*, 1993).

CONCLUSIONS

This paper represents an attempt to understand the link between coastal storms and the response of the shoreline to those storms over periods of tens to hundreds of years. Does separating erosion/recovery events due to great storms (noise) lead to a better understanding of long-term erosion trends (the signal)? Should we omit storm-influenced data from shoreline change analyses because shoreline positions are "very inconsistent with a linear trend model of shoreline retreat for an extended time interval that can reach even 10 years or more" as suggested by DOUGLAS and CROWELL (2000)? Should we revisit MORTON's (1978) suggestions to use photographs of shorelines taken during calm weather and under similar tidal conditions and consider the types and magnitudes of errors associated with using storm-influenced data in long-term shoreline trend analysis? Or, does the frequency and magnitude of storms *control* or, at least, *influence* long-term shoreline changes and, therefore, substantially contribute to the signal? If the latter is true, when do storm-influenced data points produce noise (systematic error)?

In contrast to DOUGLAS and CROWELL (2000) and HONEYCUTT *et al.* (in press), our research suggests that, based on analyses of a reach along the wave-dominated Outer Banks of North Carolina, the exclusion of storm-influenced data points is neither warranted nor prudent because such values do not constitute outliers, and they do not increase substantially the range of uncertainty surrounding predicted future shoreline positions. The added value of reducing uncertainty with the inclusion of more data points outweighs the potential advantages of excluding storm-influenced or storm-dominated data points.

Two conditions used in this analysis may not always apply to other data sets: (1) coastal reaches where storms play a lesser role in shaping and modifying beaches and (2) reaches that clearly (physically or quantitatively) display non-linear long-term shoreline movement (assumption of linearity fails). For example, large departures from the mean position (storm-influenced shorelines) on a relatively stable beach represent noise and are not part of the signal, whereas on beaches of moderate to high erosion, the storm-influenced shorelines are part or most of the signal because those beaches do not fully or temporarily recover to their pre-storm position. The most obvious examples where immediate post-storm shorelines produce a signal and not noise are muddy beaches and bluffs that show no recovery from a storm impact. Consequently, several matters deserve additional investigation: Further work using larger data sets covering a variety of hydrodynamic conditions will be needed to clarify whether this result stems from the cumulative effect of synoptic-scale storms. Attention needs to be given to quantifying the uncertainty ranges for many transects over large coastal reaches for data-sets comprising storm- and non-storm-influenced data, with and without outliers, to determine the influence of coastal storms on shoreline predictions. Alternative outlier detection methods (for outliers on y or shoreline position), such as the Winsorized t, would be valuable in confirming these findings (HAWKINS, 1980). Furthermore, a test of influence should be conducted, such as Cook's measure of distance to determine the extent to which isolated data points (in the time or x direction) influence shoreline rates of change. In addition, this analysis should be applied to data-poor regions. In summary, we recommend:

(1) Visually examining scattergrams of shoreline position/time data to detect and isolate coarse errors (outliers) which may have occurred during measurement or execution. Delete coarse errors.
(2) Retaining shoreline positions that closely follow(ed) storm events in wave-dominated coastal environments. The systematic error incorporated into such points does not appear to create outliers (*i.e.,* storms control shoreline movement), and shoreline predictions are not substantially altered.

ACKNOWLEDGMENTS

We wish to acknowledge and thank the Federal Emergency Management Agency for the financial support of this study.

We also wish to thank the anonymous reviewers for their excellent suggestions for improving this manuscript.

LITERATURE CITED

AGAR, D.V., 1980. *The Nature of the Stratigraphical Record,* 2nd edition. John Wiley and Sons, New York, 122p.

BOYD, R. and PENLAND, S., 1984. Shoreface translation and the Holocene stratigraphic record: Examples from Nova Scotia, the Mississippi Delta and Eastern Australia. *Marine Geology,* 60, 391–412.

CHORLEY, R.J. and KENNEDY, B.A., 1971. *Physical Geography: A Systems Approach.* Prentice-Hall, London, 370p.

CROWELL, M.; LEATHERMAN, S.P., and BUCKLEY, M.K., 1993. Erosion rate analysis: Long-term versus short-term data. *Shore and Beach,* 61(2), 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.

DOLAN, R.; FENSTER, M.S., and HOLME, S.J., 1992. Spatial analysis of shoreline recession and accretion. *Journal of Coastal Research,* 8(2), 263–285.

DOLAN, R. and FENSTER, M.S., 1995. *Technical Support for the Federal Emergency Management Agency's Guidelines and Specifications for Erosion Studies.* Technical Report, Modification #4 submitted by University of Virginia to the Federal Emergency Management Agency, 101p.

DOLAN, R.; LINS, H., and HAYDEN, B., 1988. Mid-Atlantic coastal storms. *Journal of Coastal Research,* 4 (3), 417–433.

DOTT, R.H., Jr., 1983. 1982 SEPM Presidential Address. Episodic sedimentation—how normal is average? How rare is rare? Does it matter? *Journal of Sedimentary Petrology,* 53, 5–23.

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

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

FENSTER, M.S. and DOLAN, R., 1996. Assessing the impact of tidal inlets on adjacent barrier island shorelines. *Journal of Coastal Research,* 12(1), p. 294–310.

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

HAMBLIN, A.P. and WALKER, R.G., 1979. Storm-dominated shallow marine deposits: the Fernie-Kootenay (Jurassic) transition, southern Rocky Mountains. *Canadian Journal of Earth Science,* 16, 1673–1690.

HAWKINS, D.M., 1980. *Identification of Outliers.* Chapman and Hall, London, 188p.

HAYES, M.O., 1979. Barrier island morphology as a function of tidal and wave regime. *In*: LEATHERMAN, S.P. (ed.), *Barrier Islands from the Gulf of St. Lawrence to the Gulf of Mexico.* New York: Academic Press, pp 1–27.

HONEYCUTT, M.G.; CROWELL, M., and DOUGLAS, B.C., in press. Shoreline position forecasting: Impact of storms, rate-calculation methodologies, and temporal scales. *Journal of Coastal Research.*

INMAN, D.L., and DOLAN, R., 1989. The Outer Banks of North Carolina: Budget of sediment and inlet dynamics along a migrating barrier island system. *Journal of Coastal Research,* 5(2), 193–237.

JENSEN, R.E., 1983. *Atlantic Coast Hindcast Shallow-Water Significant Wave Information.* U.S. Army Corps of Engineers, Waterways Experiment Station, WIS Report 9, 1000p.

KLEINBAUM, D.G., and KUPPER, L.L., 1978. *Applied Regression Analysis and Other Multivariable Methods,* Duxbury Press, North Scituate, Massachusetts, 556p.

KRUMBEIN, W.C. and GRAYBILL, F.A., 1965. *An Introduction to Statistical Models in Geology.* McGraw-Hill, New York, NY, 475p.

LEFFLER, M.W.; HATHAWAY, K.K.; SCARBOROUGH, B.L.; BARON, C.F., and MILLER, H.C., 1990. *Annual Data Summary for 1988 CERC Field Research Facility.* Technical Report CERC-90–13, v. 1, 74p.

LEATHERMAN, S.P.; WILLIAMS, A.T., and FISHER, J.S., 1977. Overwash sedimentation associated with a large-scale northeaster. *Marine Geology,* 24, 109–121.

LEOPOLD, LB.; WOLMAN, M.G., and MILLER, J.P., 1964. *Fluvial Processes in Geomorphology.* W.H. Freeman, San Francisco, 522p.

MONTGOMERY, D.C. and PECK, E.A., 1992. *Introduction to Linear Regression Analysis (2nd ed),* New York: John Wiley and Sons, Inc. 504p.

MORTON, R.A., 1978. Analysis of sequential shoreline changes. *In*: TANNER, W.F., (ed.), *Standards for Measuring Shoreline Changes.* Coastal Research and Department of Geology, Florida State University, pp 43–48.

MORTON, R.A., 1979. Temporal and spatial variations in shoreline changes and their implications, examples from the Texas Gulf Coast. *Journal of Sedimentary Petrology,* 49(4) 1101–1111.

NIEDORODA, A.W.; SWIFT, D.J.P., and HOPKINS, T.S., 1985. The Shoreface. *In*: DAVIS, R.A., Jr. (ed.), *Coastal Sedimentary Environments,* 2nd ed., Springer-Verlag, New York, NY, pp. 533–624.

SCHUMM, S.A., 1977. *The Fluvial System.* John Wiley and Sons, New York, 338p.

SCHUMM, S.A. and LICHTY, R.W., 1965. Time, space and causality in geomorphology: *American Journal of Science,* 263, 110–119.

STEVENS, J.P., 1984. Outliers and influential data points in regression analysis. *Psychological Bulletin,* 95(2), 334–344.

SWIFT, D.J.P., 1968. Coastal erosion and transgressive stratigraphy. *Journal of Geology,* 76, 444–456.

SWIFT, D.J.P., 1975. Barrier island genesis: evidence from the Middle Atlantic Shelf of North America. *Sedimentary Geology,* 14, 1–43.

THOMPSON, E., 1977. *Wave Climate at Selected Locations Along United States Coasts.* TR-77-1, U.S. Army Corps of Engineers, Coastal Engineering Research Center, Ft. Belvoir, VA.