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Change in Shoreline Position for Two Consecutive Years Using LIDAR Along the Outer Banks, North Carolina

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CHANGE IN SHORELINE POSITION FOR TWO CONSECUTIVE YEARS USING LIDAR ALONG THE OUTER BANKS, NORTH CAROLINA

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science

By

RACHEL MARIE TAYLOR
B.A., Ball State University, 2007

2012
Wright State University
I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Rachel Marie Taylor ENTITLED Change in Shoreline Position for Two Consecutive Years Using LIDAR along the Outer Banks, North Carolina BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science

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The signal of shoreline change for the Outer Banks, North Carolina is non-stationary. A baseline, west of the first line of dunes, is created for each 5 km section and shore-perpendicular profiles constructed every 20 meters in the alongshore direction. The profiles are obtained from two light detection and ranging (LIDAR) surveys performed in June 22, 2006 and July 7 and 8, 2007.

For five selected sections of coast, Fourier analysis of the shoreline change signal indicates the signal is self-affine i.e. the mean is not stationary, but changes with position along the signal (Malumud and Turcotte, 1999) with a scaling exponent that varies from 1.2 to 2.1. Four of the five selected sections of coast, Wavelet analysis of the shoreline change signal indicate the signal is self-affine with a scaling exponent that varies from 1.4 to 2.3.
The power scaling exponents extend over three orders of magnitude in length from 0.1 to 10 km.

The values of the power scaling exponent (greater than 1) indicate that the signal has no characteristic length scale and is non-stationary as the power scaling increases, low-frequency (high period) contributions dominate over high-frequency (low period) contributions. The range in power scaling exponents indicates that abrupt changes in shoreline position are less common than gradual changes over long distances (Malamud and Turcotte, 1999).
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1. INTRODUCTION

1.1 Background

Barrier islands, composed of sand sized and finer un lithified sediments transported by waves are found sporadically along the Atlantic coast of the United States (Leatherman, 1988). Most of the barrier islands have undergone intense human development during periods of relative stability in sea level rise (Fenster and Dolan, 1993). Barrier islands protect the mainland shoreline behind the islands from storm waves and erosion. The barrier islands are exposed to natural stressors such as ocean waves and ocean storms resulting in a continuously changing seaward coastline. Rising sea level makes barrier islands more vulnerable to coastal erosion and overwash during severe storm events. Understanding change in shoreline position adds to fundamental understanding of the natural process and may contribute to development of appropriate scientific and societal responses to shoreline retreat.
Traditional studies of the change of shoreline position have relied on spatially limited data sets, such as shoreline perpendicular beach topography profiles spaced hundreds or thousands of meters apart. Interpolation between such beach profiles does not produce a representative topographic sampling. The advent of LIDAR in the 1990’s, permits collection of continuous, high-resolution shoreline position data (Sallenger et al., 1999). In this study, I have measured the change in horizontal shoreline position at the 0.8-meter elevation contour by taking the horizontal difference between two shorelines extracted from LIDAR data collected at one year intervals for 2006 and 2007 at four study areas along the outer beaches of the Outer Banks, North Carolina.

1.2 Previous Work

This study builds on the work of Nelson (2001) who used LIDAR data to analysis the change in shoreline position due to storm events and weathering. Four areas of the Outer Banks were observed using two of the five geomorphologic parameters in Nelson’s study to quantify change: (1) beach width (the horizontal distance from the shoreline to the dune base) and (2) horizontal change in shoreline location, see Figure 1.
Nelson used statistical analyses to assess the morphological change in parameters of dune height and beach width for the entire coastline between two LIDAR survey dates (September 1997 and September 1998).

Nelson concluded that dune height change correlates with shoreline change, dune impact and beach width such that the wider the beach is, the less chance of dune erosion. He also theorized that dune retreat correlates with beach width during storms that are within the collision regime (section of the beach where wave runup exceeds the elevation at the base of the dune) providing that the maximum potential dune erosion during storm wave run-up within the collision regime increases as a non-
linear function with decreasing beach width using statistical comparison and that the functional relation between maximum dune erosion and beach width varies with geomorphology and/or wave climate.

Nelson study was dependent on the storm events, long-shore sand movement, and wave action that alters the shoreline. Nelson concentrated his studies on the changes on shoreline position and their correlation with the dune and beach parameters along shore perpendicular profile lines. He studied the average and variance of each geomorphic parameter for statistical comparison spatially and temporally. Nelson’s focus was on how storms that occurred between his two study dates influence each of the three areas.

Nelson also studied the morphology of the five areas and compared dune height and beach width between the two years. He looked at the area as a whole and also compared the three different areas to distinguish the ability the storms/weathering have on different beach slopes on a grand scale. In contrast to Nelson’s use of statistical analysis, this study uses Fourier and Wavelet analysis of the difference in horizontal position of the shoreline between beach length and beach width to measure the power scaling properties of the differences.
In the work of Tebbens et al., 2002, the scaling exponents of the LIDAR data collected September 1997 and September 1998 was analyzed using Wavelet analysis. The shoreline change was measured by using the horizontal change in position of the 0.8 meter contour sampled from perpendicular profiles spaced at 20 meter intervals along the beach. Tebbens study is comparable to this study, that most data preparation and the Wavelet analysis method are similar. Tebbens concluded that wavelet analysis of the shoreline change signal indicates the signal is self-affine with scaling exponent that varies from 1.2 to 2.1.

Another study quite similar with the use of Wavelet analysis was from Lazarus et al., 2011. Lazarus used shoreline change measurements from the Outer Banks to explore existing evidence that shoreline change on a sandy coast is self-affine. He confirmed that the mean variance of shoreline change can be approximated by a power law from tens of meters up to about 4-8 kilometers. Lazarus’s findings suggested there is a need for studies that target long-term, large-scale shoreline change.
2. STUDY AREA

The study area is located along the Atlantic coast of the North Carolina Outer Banks from Cape Lookout to Oregon Inlet (Figure 2).

Figure 2. Location map of the study area along the Atlantic coast of the North Carolina Outer Banks from Cape Lookout to Oregon Inlet (courtesy of USGS).
The study site is divided into three areas based on the strike of the coast and the stabilization of the dunes (Figure 3).

Figure 3. A map of the Outer Banks, NC showing the divisions into Areas 1, 2, and 3 based on shoreline strike and stabilization projects (Tebbens et al., 2002).

Area 1 is south of Ocracoke Inlet, locally known as the Core Banks. This area (estimated 77 km long) consists of low-lying vegetated sand dunes in their natural state (Figure 4). North of Ocracoke Inlet in Area 2
(approximately 47 km long) and Area 3 (approximately 65 km long). These areas had been artificially stabilized since the 1930’s using prefabricated brush and slat panels to create dune heights of 3-8 m, and dune widths of 25-100 m (Birkemeier et al., 1984) (Figure 5). Since the 1930’s annual maintenance of the dunes was neglected during the stabilization project which slowed beginning in the mid-1970’s (Birkemeier et al., 1984; DeKimpe et al., 1991).

![Figure 4. Natural dunes of Portsmouth (Core Banks) in area 1 (courtesy of USGS).](image-url)
The outer coast strikes northeast in Areas 1 and 2, from the Core Banks to south of Cape Hatteras. The coast strikes north-south in Area 3, north of Cape Hatteras. Coastline orientation can have an impact on how the shoreline erodes and accretes due to the angle between the coast and incoming waves.

2.1 Storms

Storms encountering the Outer Banks include: northeasters, tropical storms, or hurricanes. Northeasters take place during the winter months (i.e. December, January and February) and erode the coastline and eroded sediments are moved and stored in offshore sandbars. During the summer months (i.e. June, July August) the sediments are transported from offshore sandbars back on the coastline. Impacts from tropical storms and hurricanes are dependent

Figure 5. Enhanced dunes of Avon in area 3 (courtesy of USGS).
not only on the magnitude of storm forced parameters (i.e. including, but not limited to storm surge and runup) but also on the geometry of the coastline (i.e. including, but not limited to strike orientation and dune height and width) (Sallenger 2000). In between storms, there is a large and steady onshore feed of sand from the upper shoreface. Storms may cause irreversible damage to dunes, because dune building processes are very slow and mainly depend on eolian transport, such are the dunes found on the Outer Banks (Birkemeir et al., 1984; DeKimpe et al., 1991; Sallenger et al., 2000).

National Oceanographic Atmospheric Association (NOAA) tracks storms around the world and tropical cyclone reports are generated by the National Hurricane Center. For 2006 and 2007 these reports show two storms came close enough to affect the beach width and dune height of the Outer Banks between the two LIDAR collection dates, June 22, 2006 and July 7th and 8th, 2007. First was tropical storm Beryl, which existed from July 18th to 21st, 2006 and tracked about 360 km east of the Outer Banks (Figure 6). The storm surge was only about 1 ft. therefore, probably did not significantly alter beach morphology. Second was Ernesto, A category 1 hurricane, which existed August 24th-September 1st, 2006 and tracked about 200 km west of the Outer Banks (Figure 7).
Although, these storms passed between the collection dates, their degree on strength on the study area was too small to make a significant impact on this study.

Figure 6. A map of Tropical Storm Beryl’s path (from NOAA and the National Hurricane Center).
Figure 7. A map of Hurricane Ernesto’s path (from NOAA and the National Hurricane Center).
3. DATA

3.1 LIDAR

The LIDAR instrument calculates the distance from the instrument to the beach surface by the wavelength of scattered light and measuring the two-way travel time of a laser pulse, which can measure land surface elevation (Sallenger et. al., 2000). LIDAR can image a feature about the same size as its wavelength or larger making it sensitive to aerosols and cloud particles (Sallenger et. al., 2000). Beach topographic features are readily distinguished, but the LIDAR breaks down at and near the sand/water interface because of the water aerosols created by breaking waves (Sallenger et. al., 2000). Water saturated sand in the swash zone scatters the LIDAR signal so that there are no returns. The shorelines used in this study are at 0.8 meters elevation which is above the sand/water interface.

LIDAR data used in this study were collected with Nation Aeronautics and Space Administration’s (NASA)
Airborne Topographic Mapper (ATM) as a part of a cooperative effort between NASA, U.S. Geological Survey (USGS), and the National Oceanographic and Atmospheric Administration (NOAA). An ATM, Optech 1233 ALTM LIDAR instrument mounted in a twin engine Cessna 337, collected the data used in this report.

The ATM recorded measurements at rates of 2,000 to 5,000 pulses per second with a vertical precision of about 15 centimeters and horizontal precision of 0.5 meters (Figure 8) (Sallenger et al., 2003). A survey window with both a low PDOP (strong satellite geometry) and low tide achieved as best as possible (Tebbens, 2006). Cape Hatteras was reported to have a low tide at 11:02AM on June 22 (Berkeley Group NCALM). The June 22, 2006 survey was taken from 10:10AM – 1:30PM, which includes a degraded PDOP from 12:15PM – 12:45PM (Berkeley Group NCALM). The degraded PDOP would be considered a moderately strong satellite geometry, meaning that the quality of data returned was not the best but still acceptable. Three flight passes were flown by eye to cover the beaches as needed. One pass was flown at 1500m above ground level (AGL) and two others were flown at 600m AGL with a scan parameter set at 28Hz scan frequency and ±18° scan angle.
A swath 974 meters wide was recorded for the flight at 1500 meters AGL, while a swath of 390 meters wide was recorded for the flight at 600 meters AGL. Two ground-based GPS vehicle survey stations, Buxton, NC (BUXT) and Beaufort airport (BEAU), were used to estimate lidar-based shoreline position.

Figure 8. Sketch of a NOAA DeHavilland Twin Otter making three flight passes were taken to cover the entire coastline; one pass was flown at 1500m above ground level (AGL) and the two others flown at 600m AGL (modified from Sallenger et al., 1999).
3.2 Instrumental Errors

Previous studies, such as Sallenger et al. (2000) conducted a study in Duck, NC to evaluate the vertical precision of the ATM. The study concluded that the vertical precision of the ATM is a root mean square (RMS) of about 15 centimeters. Sallenger et al. (2000) also concluded from a further study that the mean error from drift can be up to ±13 centimeters. Using LIDAR data, Sallengenger et al. (2001), has shown that a topographic map can be created with a vertical precision of roughly 15 cm with the precision of the laser at about ±0.5 m.

3.3 Shoreline Change Data

Figure 9a plots the shoreline change observed in June 2006 and July 2007 as a discrete time series. The changes in shoreline position, y-axis, in meters, are positive integers for accretion and negative integers for erosion. Drum Inlet, Figure 9a, can be located near x = 35 km by the larger magnitude fluctuations in shoreline change on y-axis. Area 1 time series was split into two smaller segments on either side of x = 35 km, Area 1.1 and Area 1.2, (Figure 9b and Figure 9c). The length of shoreline for these two areas is 24 km and 18 km respectively.
Figure 9a. Plot of the differences in distances of shore-perpendicular profiles between June 2006 and July 2007 for all of area 1 (see Figure 12). The x-axes is shore-parallel position in kilometers and the y-axis is the net change in shoreline position, positive values represent horizontal accretion; negative values represent horizontal erosion.
Figure 9b. *Plot of the differences in distances of shore-perpendicular profiles between June 2006 and July 2007 for area 1.1 (see Figure 12). The x-axes is shore-parallel position in kilometers and the y-axis is the net change in shoreline position, positive values represent horizontal accretion; negative values represent horizontal erosion.*
Figure 9c. Plot of the differences in distances of shore-perpendicular profiles between June 2006 and July 2007 for area 1.2 (see Figure 12). The x-axes is shore-parallel position in kilometers and the y-axis is the net change in shoreline position, positive values represent horizontal accretion; negative values represent horizontal erosion.

After Ocracoke Inlet, another 18-km segment north of Portsmouth, Area 2.1 (Figure 13), was extracted from of Area 2 (Figure 12). In Area 2.1 at approximately 25 km, Hatteras Inlet can be observed. A segment after the inlet, from 30 km to 44 km would have been analyzed but difficulties with the data caused problems with data extraction from ArcGIS. The processed data received (from Berkley University, California) was corrupt, therefore was not able to be used.
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Figure 9e. *Plot of the differences in distances of shore-perpendicular profiles between June 2006 and July 2007 for the first part of area 2 (see Figure 12). The x-axes is shore-parallel position in kilometers and the y-axis is the net change in shoreline position, positive values represent horizontal accretion; negative values represent horizontal erosion.*

North of Cape Hatteras, Area 3 (Figure 9f), two segments were extracted, Area 3.1 and Area 3.2, for analysis. Area 3.1 extends from 6 km to 32 km for a total shoreline length of 26 km (Figure 9g), and Area 3.2 extends from 42 km to 61 km with a shoreline length of 19 km (Figure 9h). Some difficulties with data at the end Area 3.2 arose when processed the data through the fortran code. The data series for Area 3.2 is appears to be noisy and corrupted, thus no further data analysis will be completed.
Figure 9f. Plot of the differences in distances of shore-perpendicular profiles between June 2006 and July 2007 for all of area 3 (see Figure 12). The x-axes is shore-parallel position in kilometers and the y-axis is the net change in shoreline position, positive values represent horizontal accretion; negative values represent horizontal erosion.
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Figure 9h. Plot of the differences in distances of shore-perpendicular profiles between June 2006 and July 2007 for area 3.2 (see Figure 12). The x-axes is shore-parallel position in kilometers and the y-axis is the net change in shoreline position, positive values represent horizontal accretion; negative values represent horizontal erosion.
4. METHOD OF DATA PREPARATION AND ANALYSIS

4.1 Data Preparation

Pre--filter analysis of the LIDAR data was performed by Ionut Lordache from University of California, Berkeley. Coordinates were set to NAD83 and UTM Zone 18. Pre-filtering and processing of this data set included a “bare-earth” dataset generated by using Terrasolid’s TerraScan software and the “high pass” (higher plane altitude) and “low pass” (lower plane altitude) were processed as two separate datasets. Each data set was run through a classification routine consisting of three algorithms, removal of “low points”, ground classification, and below surface removal. This filtering, processing and classification was completed at the University of California at Berkeley.

Processors at the University of California at Berkeley removed “low points” which searched for possible error points that are below the ground surface. Comparisons of points within a given neighborhood were used to verify if a point was lower than any other.
The next processing step taken by the Berkeleys staff was ground classification which classifies ground points using a triangulated surface model. The classification helps keep low buildings out of the model and helps avoiding unnecessary point density by reducing the eagerness to add new points to ground inside a triangle with all edges shorter than a specified length.

Below surface removal classifies points which are lower than neighboring points. It is similar to the removal of "low points computer program" but was run after ground classification. This algorithm finds up to 25 closest neighboring source points and fits a plane through them.

After the two classifications, the ground points were output into longitudinal tiles with a 60 m overlap, saved in ASCII format (XYZI), and gridded at a 1 m cell size.

Output data was uploaded as raster files (grid data) into ArcGIS. The study area was divided into three areas (Area 1, Area 2, Area 3) based on the strike of the coast and the stabilization of the dunes and then subdivided into approximately 5-km sections, or a shorter or longer distance in which a shore-parallel line could be created. An elevation of 0.8 m was located on the LIDAR elevation map using 3D analyst which was a modified direction from
Tebbens et al. (2002). The mean sea level elevation was 0.8 m above sea level for the two surveys used in this study as well for the surveys analyzed by Tebbens et al, (2002), making comparisons between each survey possible.

4.2 Shore Perpendicular Profiles

A baseline, west of the first line of dunes, was created for each 5-km section. Shore-perpendicular lines were constructed every 20m in the alongshore direction for both 2006 and 2007. Shore perpendicular lines were for each 5-km section. GPS points used for the perpendicular lines were collected using ExpertGPS software (no publisher). The points at 20m intervals on either side of the shore line were exported from ExpertGPS into Excel. These 20m interval points were organized into a table. Once this table was uploaded into ArcGIS, an extension for ArcGIS called XToolsPro (http://www.xtoolspro.com/) was used to connect the correlating shore-perpendicular points creating a "ladder- like" structure composed of a straight line inputted by the processor between the correlating shore-perpendicular points". The perpendicular lines were converted to a 3Dimensional feature using 3D Analyst on ArcGIS. Elevation data was extracted along each perpendicular line, this is achievable due to the
information collected and converted to raster data. After conversion, the elevation data was tabulated to find tendencies. This was accomplished by plotting each 20 meter section was plotted as a graph. The data, distance versus time, of the profile graph was exported as a text (.txt) file to open as an Excel workbook.

4.3 Fortran and Time Series

A fortran code created by Dr. Sarah Tebbens was used to process each profile line using the data exported into Excel. Fortran is a formula translating system that opened each profile data set and read into arrays, with an X, and Y location for each pair of values. The code systematically read the first row into the first line of each array, then moved on and read the second line into the second line of array. It kept going until the entire file was read. The fortran code expected a certain format in all profile files. Each file needed a header row in the first row with all data following in each column. After being processed, this data from the fortran code can export distance the information on the profile where the shoreline (0.8m) was located, in a text format. The differences in distance (in meters) between the two shorelines from year 2006 to 2007 are labeled as a positive integer for
accretion and negative integer for erosion. These values were uploaded into Excel and the corresponding distance along (the X value) the coastline was entered in for each value. A discrete time series plot was created with the difference in distance values between the two shoreline positions plotted as the Y-variable and the distance along coast (southern end) as the X-variable. The sequence of x,y pairs were listed in an excel sheet, ready for analysis. A discrete time series consists of a sampling sequence corresponding to an associated sampling rate.

4.4 Wavelet Analysis Method

The Wavelet analysis method, as described in Malamud and Turcotte (1999), is used to measure the power law variance of the wavelet transform.

In the wavelet method, the data time series, \( f(t') \), is convolved with a Mexican Hat wavelet transform filter using a second derivative Gaussian distribution function, \( g(t') \), in the scale parameter, \( a \), of 1, 2, 4, 8, and 16 (Malamud and Turcotte, 1999).

Second derivative Gaussian distribution form:

\[
g(t') = \left( \frac{1}{2\pi} \right)^{\frac{1}{2}} (1 - t'^2)e^{-\frac{t'^2}{2}}
\]
Each of those scales are plotted as a power law variance with x-axis as effective filter width (scale parameter, $a$, of 1, 2, 4, 8, and 16) and y-axis as variance of transforms (Malamud and Trucotte, 1999). The convolved wavelet transform, $W(t,a)$, is of the form:

$$W(t,a) = \left(\frac{1}{2\pi}\right)^{1/2} \int_{-\infty}^{\infty} \left[1 - \left(\frac{t' - t}{a}\right)^2\right] e^{-\frac{(t'-t)^2}{2a^2}} f(t')dt'$$

The wavelet transform is Self-affine, scaled by different amounts in the “x” and “y” directions, if there is a power law relationship between the variance of the wavelet transform and the effective filter width (Tebbens et al., 2002). A time series is defined to be self-affine if its power-spectral density scales as a power of their frequency (Malamud and Turcotte, 1999).

A Brownian motion is a random drift of a point or an item and has a scaling exponent, $\beta$, of about 2.0. The wavelet analysis method is demonstrated in Figure 10 using a time series that is a Brownian motion for which $\beta=2$ (Malamud and Turcotte, 1999). The time series, $f(t')$, is convolved with wavelets of different widths, $g(t')$, produced by using different values of $a$ to produce wavelet transforms $W(t,a)$, where $t'$ is the variable of the signal,
the filter is centered at \( t \), and \( a \) is the scale parameter that determines the width of the filter (Figure 10) (Tebbens et al., 2002). Lambda (\( \alpha \)) is a scale parameter that determines the width of the filter (Malamud and Turcotte, 1999). In the example shown in Figure 10, there is a power law relation, \( V \sim \lambda^\beta \), indicating the signal is self-affine (Tebbens et al., 2002). The scaling exponent, \( \beta \), equals 1.9, approximately equal to the \( \beta \) value of a Brownian motion (Malamud and Turcotte, 1999).

Figure 9. Graphical diagram demonstrating the steps performed in a wavelet analysis. A Brownian motion signal
(a) is convolved with Mexican hat filters (b) to create the wavelet transform (c). There is a power law relationship between the variance of the transforms and the effective filter width indicating that the signal is self-affine with slope, $B$, equal to 1.09 (d) (Tebbens et al., 2002).

Wavelet analysis method as described above is used to determine variance as a function of effective filter width, Lambda. In this method the data time series is convolved with a Mexican Hat wavelet transform filter (Figure 11) using a second derivative Gaussian distribution function in the scale parameter of 1, 2, 4, 8, and 16, in each segment.

Figure 10. Plot of Mexican Hat, $g(t')$,

Wavelet analysis provides a spatial resolution which the Fourier transform cannot. It provides information on both the spatial and frequency dependence of a time series (Malamud and Turcotte, 1999).
4.5 Fourier Transform Analysis Method

The method of Fourier analysis is used in conjunction with wavelet analysis to validate the beta results from each analysis. Fourier analysis requires windowing and detrending of the signal in order to calculate $\beta$. For the Fourier Transform analysis method, an Excel spreadsheet containing the difference in shoreline position time series data was imported into AutoSignal version 1.7, created by SeaSolve Software, Inc., to perform a Fourier Transform analysis of the data. The Power Spectral Density (PSD), how a power of a signal is distributed with frequency, values are then calculated using this software program.

4.6 Binning

From the Fourier Transform, the calculations are exported back into an Excel spreadsheet template, provided by J. Smigelski, 2009, is used to logarithmically bin the PSD versus period data (on period) and calculate the mean value of PSD in each bin. The binned results are then fitted by best fit power function of the form $y=ax^b$, the slope of which is beta, the scaling exponent.
4.7 Residuals

Residuals of each of the analyzed segments were performed to determine if the power function fit is optimal. This was completed using Excel. The data was selected and then was run through residuals on the data analysis option. $R^2$ is the goodness of fit parameter, the closer to the value of 1.0, the better the line fits.
5. RESULTS

5.1 Time Series Analysis

Wavelet analysis and Power Spectral Density analyses were performed on the shoreline change data set for the five areas shown in Figure 12. Each of the 5 areas is broken down into shore perpendicular sections spaced 5-km apart (not shown in Figure 12).

Figure 11. Map showing the location of the study Areas 1.1, 1.2, 2.1, 3.1, and 3.2 along the Outer Banks of North Carolina.
5.2 Wavelet Analysis

The Wavelet analysis of the shoreline change signal for Area 1.1, Area 1.2, Area 2.1, and Area 3.1 is shown in Figure 13a-13d.

Figure 12a. Wavelet analysis of shore-perpendicular horizontal shoreline change for Area 1.1 applying the wavelet method shown in Figure 11. The shoreline change signal (bottom line) and five wavelet transforms of the signal obtained by convolving with the Mexican hat filters (from bottom to top, the Mexican Hat wavelet transform filter is equal to 1, 2, 4, 8, and 16).
Figure 13b. Wavelet analysis of shore-perpendicular horizontal shoreline change for Area 1.2 applying the wavelet method shown in Figure 11. The shoreline change signal (bottom line) and five wavelet transforms of the signal obtained by convolving with the Mexican hat filters (from bottom to top, the Mexican Hat wavelet transform filter is equal to 1, 2, 4, 8, and 16).
Figure 13c. Wavelet analysis of shore-perpendicular horizontal shoreline change for Area 2.1 applying the wavelet method shown in Figure 11. The shoreline change signal (bottom line) and five wavelet transforms of the signal obtained by convolving with the Mexican hat filters (from bottom to top, the Mexican Hat wavelet transform filter is equal to 1, 2, 4, 8, and 16).
Figure 13d. Wavelet analysis of shore-perpendicular horizontal shoreline change for Area 3.1 applying the wavelet method shown in Figure 11. The shoreline change signal (bottom line) and five wavelet transforms of the signal obtained by convolving with the Mexican hat filters (from bottom to top, the Mexican Hat wavelet transform filter is equal to 1, 2, 4, 8, and 16).
For all of the areas a power function is a good model for the relationship between variance and the effective filter width, Lambda. The plots of variance vs. Lambda are shown in Figure 14a-d. The scaling exponents are shown in Table 1.

The Wavelet analyses reveal the spatial resolution of the frequency content along the sectioned shoreline. The Wavelet values for the four segments ranged from 1.4 to 2.3 (Table 1).

Table 1. A table showing each section, beach length, and the $\beta$ value from Wavelet analysis.

<table>
<thead>
<tr>
<th>Section Number</th>
<th>Nominal Length (km)</th>
<th>Wavelet $\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>24.0</td>
<td>1.9</td>
</tr>
<tr>
<td>1.2</td>
<td>18.0</td>
<td>1.7</td>
</tr>
<tr>
<td>2.1</td>
<td>18.0</td>
<td>1.4</td>
</tr>
<tr>
<td>3.1</td>
<td>26.0</td>
<td>2.3</td>
</tr>
</tbody>
</table>
Figure 14a. A plot of variance of the wavelet transform, $V_w$, versus effective filter width, $\lambda$, for Area 1.1. The relation between variance and effective filter width is well fit by a power function, indicating that shoreline change is a self-affine signal with scaling exponent of 1.9.
Figure 14b. A plot of variance of the wavelet transform, $V_w$, versus effective filter width, $\lambda$, for Area 1.2. The relation between variance and effective filter width is well fit by a power function, indicating that shoreline change is a self-affine signal with scaling exponent of 1.7.

$y = 4.46x^{1.7}$

$R^2 = 0.99$
Figure 14c. A plot of variance of the wavelet transform, $V_w$, versus effective filter width, $\lambda$, for Area 2.1. The relation between variance and effective filter width is well fit by a power function, indicating that shoreline change is a self-affine signal with scaling exponent of 1.4.

$$y = 8.36 \lambda^{1.4}$$

$$R^2 = 0.99$$
Figure 14d.  A plot of variance of the wavelet transform, \( V_w \), versus effective filter width, \( \lambda \), for Area 3.1.  The relation between variance and effective filter width is well fit by a power function, indicating that shoreline change is a self-affine signal with scaling exponent of 2.3.

5.3 Power Spectral Density, Binning and Residuals

The Power Spectral Density results for the four areas studied are shown in Figure 15a-d.  The result for Area 1.1 is shown in Figure 15a.  Note that the points plotted are not fit by a single power function, but two power functions.  The shorter segment (wavelengths less than 1000m) is an artifact of the Fourier analysis caused by phase noise and can be corrected by windowing shore perpendicular profile data (Malamud and Turcotte, 1999).  The artifact could be theorized to be real, created by the differences in strike of coastline along the beach.  A Beta
of 2.0 is found for the longer segment. A residual slope near zero shows that the power function is a good fit.

Figure 15a. Plot of area 1.1 power spectral density vs. wavelength in meters. The portion of the spectrum shown in blue is neglected in the fitting of the power function. The periodogram is well described by a power function (red line), indicating that the signal is self-affine. The scaling exponent, \( \beta \), is 2.0. The bottom line is the residuals as a function of wavelength.
Figure 15b. Plot of area 1.2 power spectral density vs. wavelength in meters. The portion of the spectrum shown in green is fitted by the power function. The periodogram is well described by a power function (red line), indicating that the signal is self-affine. The scaling exponent, $\beta$, is 1.6. The bottom line is the residuals as a function of wavelength.
Figure 15c. Plot of area 2.1 power spectral density vs. wavelength in meters. The portion of the spectrum shown in green is fitted by the power function. The periodogram is well described by a power function (red line), indicating that the signal is self-affine. The scaling exponent, $\beta$, is 1.2. The bottom line is the residuals as a function of wavelength.
Figure 15d. Plot of area 3.1 power spectral density vs. wavelength in meters. The portion of the spectrum shown in blue is neglected in the fitting of the power function. The periodogram is well described by a power function (red line), indicating that the signal is self-affine. The scaling exponent, $\beta$, is 2.1. The bottom line is the residuals as a function of wavelength.
Binning was applied to the power spectral density plots as described in the methods section. The results of binning were inconclusive and not used further in the study. However, these results can be seen in Appendix B.

The Wavelet analysis and Power Spectral Density analysis show the four shoreline areas to be self-affine. All of the scaling exponents Beta are shown in Table 1. The results of Wavelet analysis of 1997 and 1998 shoreline change for the same areas by Tebbens et al. (2006) are also shown in Table 1 for comparison.

Table 2. A table showing each section analyzed in this paper showing length along shoreline, and β value of the original data. *Indicates results from Tebbens et al. (2002).

<table>
<thead>
<tr>
<th>Section Number</th>
<th>Nominal Length (km)</th>
<th>Wavelet* β</th>
<th>Wavelet β</th>
<th>Fourier β</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>24.0</td>
<td>1.65</td>
<td>1.9</td>
<td>2.0</td>
</tr>
<tr>
<td>1.2</td>
<td>18.0</td>
<td>1.48</td>
<td>1.7</td>
<td>1.6</td>
</tr>
<tr>
<td>2.1</td>
<td>18.0</td>
<td>1.24</td>
<td>1.4</td>
<td>1.2</td>
</tr>
<tr>
<td>3.1</td>
<td>26.0</td>
<td>2.08</td>
<td>2.3</td>
<td>2.1</td>
</tr>
</tbody>
</table>
6. DISCUSSION

The change in shoreline position between June 22, 2006 and July 7 and 8, 2007 is well fit, for each of the four shoreline segments studied, by a power function over three orders of magnitude in length (from 0.1 to 10 km). This indicates that the change in shoreline position is self-affine and has no characteristic length scale (Malamud and Turcotte, 1999). The Power Spectral Density scaling exponents Beta range from 1.04 to 2.11 (Tebbens et al., 2002). As the $\beta$ values increase, low-frequency (high period) contributions dominate over high-frequency (low period) contributions. The range in $\beta$ values, Table 1, indicates that abrupt changes in shorter distance along shore are less common than gradual changes in longer distances along shore (Malamud and Turcotte, 1999). A $\beta$ that is greater than one is considered nonstationary, meaning that the mean is not constant, but changes with position along the signal (Malamud and Turcotte, 1999). The characteristic Beta value for the process of diffusion is 1.5.
7. CONCLUSIONS

The pattern of shoreline change for the four sections of the Outer Banks shoreline, ranging from 18-26 km in length, are all found to be self-affine. The scaling exponents are all greater than 1, indicating that the annual shoreline change is non-stationary which means the mean is not constant. Two of the four sections exhibit $\beta$ values near 2.0 (Area 1.1 and Area 3.1). The example of a signal with $\beta = 2$ is a random walk formed by the running sum of a coin flip. A signal with $\beta = 2$ indicates that change at each location is a random value, but has a short range and long range correlation with other locations within each study region. The other segments, have $\beta$ values between 1.2-1.6, may indicate a stochastic diffusion process which has a $\beta$ of $\approx 1.5$.

As seen in Table 1, the pattern of $\beta$ values increase from south to north (with Area 3.2 dismissed and Area 1.1 an anomaly to the pattern). This is also seen for both the annual change analyzed in Tebbens et al. (2000) and for the results of this study, with approximately the same $\beta$ values describing annual change for both annual time intervals.
8. APPENDIX A

8.1 References


Leatherman, S. P., 1988, Barrier Island Handbook, Coastal Publications Series: College Park, Maryland, University of Maryland, 92 p.


Tebbens, Sarah, Coasts in Motion: Quantifying the patterns of coastal change using LIDAR, Wright State University.
Plot of the same data, Area 1.1, as in Figure 15a, Power Spectral Density vs. Wavelength in meters. The PSD was binned with a logarithmic bins and fit with a power function. The scaling exponent Beta is 2.5 and signal is self-affine.
Plot of the same data, Area 1.2, as in Figure 15a, Power Spectral Density vs. Wavelength in meters. The PSD was binned with a logarithmic bins and fit with a power function. The scaling exponent Beta is 0.8 and signal is self-affine.
Plot of the same data, Area 2.1, as in Figure 15a, Power Spectral Density vs. Wavelength in meters. The PSD was binned with a logarithmic bins and fit with a power function. The scaling exponent Beta is 0.8 and signal is self-affine.
Plot of the same data, Area 3.1, as in Figure 15a, Power Spectral Density vs. Wavelength in meters. The PSD was binned with a logarithmic bins and fit with a power function. The scaling exponent Beta is 1.5 and signal is self-affine.