Coastal evolution is a complicated process, for it is influenced by various sub-processes and each sub-process such as waves and storms is difficult to well explain and model. To better understand the evolution process, data from several monitoring projects are analyzed with the objective of revealing evolutionary processes. The major focused fields are involved with shoreline changes, coastal geomorphology changes, and wave/storm induced erosion.

This study focuses on the shoreline downdrift of Oregon Inlet, NC. The shoreline data, topography data, wave/tide records have been utilized and become the basis of this study. In order to estimate the coastal changes for the period from 1989 to 2009, a methodology has been created to rectify the wet/dry shoreline, and statistical models have been applied to the shoreline data to characterize the shoreline change pattern and rate. Furthermore, the geomorphology changes alongshore have been coupled with the storm surge and wave runup processes, based on the statistical models. The occurrence probability of dune failure has been estimated by the Logistic Regression model for the prediction purpose. Finally, since all the coastal changes are driven by wave and storm processes, the numerical wave model SWAN have been implemented on order to estimate the nearshore wave climate and attempt correction of shoreline processes.

The results show that the shoreline change near Oregon Inlet has strong temporal correlation and periodicity, and the strength of these characteristics decreases after 2.65 miles southward. Principal Component Analysis revealed the spatial variation of shoreline change is highly
concentrated on the first 20 transects and the temporal variation of that mostly exits before 1994 and after 2002. These important findings have been well explained by the beach nourishment projects and storm events. In addition, the shoreline change rate also varies from Oregon Inlet to its south, i.e., the general trend of erosion rate increases from the Oregon Inlet to its south about 2 miles, then decreases for another 2 miles, and increases for the last 2 miles. Furthermore, the geomorphology analysis during a storm suggests that the ratio of effective water level over dune crest height, square root of dune profile area and dune height are the three major factors which mostly determine the occurrence of dune failure. At last, the wave simulations by seasons have explained the seasonality of nearshore waves as well as the spatial variability of wave energy distribution alongshore. The general trend of wave energy is increasing as it goes from the Oregon Inlet to its south, with the exception at about 2 miles south of Oregon Inlet, in which the wave energy has a sharp decrease. Besides, the wave simulation during Hurricane Isabel suggests that waves have higher energy at the east of Oregon Inlet, and have dominant wave direction from the southeast to northwest. Finally, the cross-correlation analysis has shown that about 64% of the shoreline change variance can be explained by the significant wave height and $d_{50}$. As a result, wave energy and sediment size are two major factors causing shoreline changes during the Hurricane Isabel.
Estimation of Coastal Evolution through Coupled Wave Modeling and GIS Techniques

by
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A dissertation submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the degree of Doctor of Philosophy

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BIOGRAPHY

Qiang Jin was born in Xi’an, Shaanxi, China. He received his BS degree and MS degree in Environmental Science and Engineering, from Tsinghua University in 2003 and 2006 respectively. He was enrolled in the graduate program at NC State University in the fall of 2006 and received his MS in Statistics in 2009.
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Chapter 1 Estimation of Coast Change Pattern and Rate through the Rectified Shorelines based on Statistical Models

Abstract

The coast geomorphologic pattern is crucial, for its protection of the structures and residence from being damaged by washover. Among all the geomorphologic indicators, shoreline is one of the most important factors. It is of importance for coastal management, especially for the design of building setback lines. However, its position is difficult to determine due to the fluctuation of water surfaces. In addition, the traditional linear method for shoreline change is not a good estimation due to the complexity of shoreline change pattern over time. As a result, it is essential to establish a methodology which can have the shoreline data rectified and capture the correct shoreline change pattern.

The shoreline at the east coast of North Carolina is experiencing erosion from time to time. Its geomorphologic properties have been changed greatly due to both natural processes and human activities. In this study, the Oregon Inlet region has been chosen as the study area, for its important location and special hydraulic pattern. The time series of shoreline data were obtained from the delineation of wet/dry line alongshore on the aerial photos, which is from 1989 to 2009 at a time interval of six-month. A widely applied wave runup model was introduced to this study and used to estimate the water surface fluctuation due to the variation of wave conditions. The tide data was collected according to the flight time when the aerial photos were taken, and used to rectify the vertical shift of water surface. The total vertical shoreline shift due to the water level was transformed into the horizontal shoreline shift based on the foreshore slope, which was extracted from the ground survey data of beach profile. The shoreline was then rectified through the Linear Referencing techniques according to the estimation of horizontal shoreline shift. Finally, the shoreline change pattern over time was captured by the ARMA model and periodogram analysis, while the spatial and temporal variations were characterized by the Principal Component Analysis (PCA). In addition, the change rate was estimated through the Autoregressive Error Model, which takes into account the temporal correlation between time series datasets.
The results show that temporal dependency, as well as periodicity of shoreline changes exists from the Oregon Inlet to its south about 2.65 miles. The temporal dependency of shoreline change is significant for the first 2.65 miles, but not from the 2.65 miles point southward. Periodogram analysis indicates the most common periods of shoreline change are about 1.25 to 5 years. The temporal and spatial variations of shoreline changes were captured by PCA, which suggests the shoreline changes are relatively intensive before 1992 and after 2002 for the first 20 transects (2.65 miles from Terminal Groin of Oregon Inlet). The major reason for this variation is due to the beach nourishment project and storm events. In addition, spatial variation of shoreline change rate also exists from the Oregon Inlet to its south, i.e., the general trend of erosion rate increases from the Oregon Inlet to its south about 2 miles, then decreases for another 2 miles, and increases for the last 2 miles. Compared with the AEM method, the traditional OLS method has overestimated the linear shoreline change rate by ignoring the temporal dependency of residuals.

**Key words:** Shoreline, Wave Runup, ARMA, Periodogram, PCA
1 Overview

Shoreline is the interface of the land and body of water. It plays an important role not only in coastal resource management and navigation, but also the design for building setback lines. Waves behave on the coast and result in coastal erosion and accretion. The shoreline erosion has being threatened the community infrastructure from time to time. Engineers also employ shoreline and beach morphology information for designing coastal and shipping structures. As a result, coastal engineers have recognized the usefulness of the shoreline information for studying coastal erosion and accretion (Dolan, et al., 1991; Morton, et al., 2005).

1.1 Shoreline definition and derivation

Generally, an idealized shoreline refers to a spatial continuous line of the interface between the land and waters (Boak, et al., 2005; Parker, 2001). However, in reality, this simplified definition is a challenge to apply, because the interface between land and water often moves up and down due to the tide level and runup. In the last century, aerial photogrammetry has been well developed and used as the primary shoreline mapping technique (Fisher and Overton, 1994; Graham, et al., 2003). Shoreline data can be generated precisely via orthophotos at a high time resolution. However, the shorelines generated on the orthophotos are defined as the interface of the land and water, i.e., the wet/dry line. The big issue regarding the wet/dry line is that it only can reflect the most recent water line position at that specific moment. This line may be created due to the high tide or an instant wave runup, but may not reflect the real coastal characteristics due to the sand transport. The second issue is that, the drawing of shoreline based on the orthophotos is fairly subjective, and may not be applicable where the coastal environment is complex. The fundamental issue associated with the two factors may results in shoreline change due to the temporary water level change, or the subjectivity of the drawer, other than the actual coastal erosion or accretion. Therefore, a constant and objective shoreline definition is needed as to be used for coastal erosion and accretion estimation.
The mean high water line (MHWL) is usually treated as the legal shoreline by many U.S. government agencies, including the U.S. Army Corps of Engineers, U.S. Geological Survey, and the U.S. Census Bureau (Graham, et al. 2003). The MHWL is the position of water and land interface, where the land elevation is equal to the mean high water (MHW) tidal datum. In recent decades, modern geospatial techniques have been well developed, such as real time kinematic GPS, remote sensing (RS), and Geographic Information System (GIS). These techniques can be applied to coastal topographic analysis, including coastal mapping and shoreline detection. A special terrain RS technique called LIDAR (airborne LIght Detection And Ranging) is one among all those techniques. It has a high spatial resolution and can derive the Digital Elevation Model (DEM) with a resolution of up to 1 ft (Robertson, et al., 2004). The National Oceanic and Atmospheric Administration Coastal Services Center (CSC) have collected topographical LIDAR data along the U.S coastline through a partnership program with the U.S. Geological Survey (USGS) Center. With these LIDAR data, DEM can be easily interpolated and generated in some GIS (Mitasova and Overton, 2005). As a result, shoreline defined as the MHWL can be extracted from the DEM by using the MHW tidal datum. However, the big issue associated with this method is that, the LIDAR data is very limited with a low temporal resolution, about 1 dataset per year. In addition, this technique was not well developed until recently. It is not applicable for the researcher to study the history of coastal evolution. Thus, this technique alone may not be well applied when the coastal evolution is the focus of our interest.

1.2 Shoreline change rate and pattern

Furthermore, the estimation of shoreline change rate and the prediction of shoreline position should be further discussed, for the complexity of shoreline change and some assumption cannot be satisfied in reality. The shoreline change rate may not necessarily be linear, and may have temporal correlations at any points in the time series history. In addition, the traditional estimation of shoreline change rate cannot capture the details of shoreline change pattern, i.e., both the change rate and change pattern cannot be well characterized in the same model.
Dean, et al. (1999) applied three shoreline change rate methods – OLS (Ordinary Least Square linear regression), EPR (End Point Rate), and AOR (Average of Rates) to mapping Florida’s hazard zones. They compared these methods by computing their correlation coefficient. Finally, the OLS was chosen as their preferred method. Honeycutt, et al. (2001) compared EPR to OLS by predicting known historical shoreline data. They confirmed that the accuracy of shoreline change rates improves without storm influenced data points, and concluded that OLS better predicts shorelines than EPR. Genz, et al. (2007) calculated erosion rates using EPR, OLS, JK (Jack Knifing) as well as AOR, and compared their advantages for the same dataset. All four methods resulted in similar rates, but AOR was identified as the most appropriate shoreline change rate method at Rincon.

For the four proposed methods above, they are applicable only under some certain conditions. The EPR uses only two data points to delineate a change rate - the earliest and most recent shoreline positions. Thus the information contained in other data points is entirely omitted and is very sensitive to the start point and the end point of the time series data. The AOR averages the long-term change, excluding changes due to measurement errors. It filters out short term change by a minimum time criterion. However, the minimum time criterion can mislead the result, for the AOR is sensitive to how the minimum time criterion was chosen. OLS fit can provide a long-term trend over the years, but shoreline change is not constant, and the result is very sensitive to the outliers, which means the Gaussian assumption is violated (Zhang, et al., 2002). The JK method uses multiple OLS fits to determine the shoreline change rate. A different point for each line is omitted, resulting in a different slope for each line. The slopes are averaged to provide a shoreline change rate. However, the computation of each possible linear trend is not efficient.

In reality, shoreline change is a complicated process with some nonlinearity attributes, and it does not recede or accrete in a uniform manner. Both spatial variations and temporal variations exist in the shoreline change. As a result, using only a constant change rate will neither satisfy the assumption of constant slope for those linear models, nor fully capture the characteristics of shoreline changes. Also, the efficiency of parameter estimates will be
adversely affected and standard error estimates will be biased if the residual term is autocorrelated. In order to improve the traditional methods, several advanced statistical techniques have been well applied to the shoreline change data. Hansen et al. (2010) has applied the EOF (Empirical Orthogonal Function) analysis to the sub-aerial beach survey data, in order to capture the temporal and spatial variations of shoreline change, in addition to the standard linear regression analysis. Buonaiuto, et al. (2008) applied the spatial Principal Component Analysis (PCA) to five bathymetric surveys of Shinnecock Inlet to identify the dominant change pattern of morphology, and finally explore the driving forces behind the observed evolution of the ebb shoal complex. In addition, as a type of time series data, the changes of shoreline position may have temporal dependency, and consequently follow a special time series model, such as Auto Regressive and Moving Average (ARMA). For example, the post shoreline position depends on prior shoreline positions because of the sand disposal project or the storm event. Also, periodicity of shoreline change may exist in the residuals, for the seasonal wave climate may dominate the change pattern to some extent.

Finally, the objective of this study is to create an efficient methodology for rectifying shoreline position as to eliminate the wave and tide effects. Moreover, the shoreline change rate and pattern will be characterized based on the statistical models.
2 Theory review

2.1 Linear wave transformation

Linear wave theory is also called the small-amplitude or Airy wave theory. It gives a reasonable approximation of wave characteristics for a wide range of wave parameters. Generally, the wave period ranges from about 3 to 25 seconds. Linear wave transformation is based on the linear wave theory, in which only wave shoaling and refraction processes are considered. This transformation, with water depth at only reference point and destination, is useful when there is no detailed bathymetry data and wave climate data in the transition area between the reference point and the destination. Although more complex wave cannot be well explained by the linear wave theory, the linear wave transformation can still be a good approximation under certain conditions and assumptions.

In the linear wave theory, the transformed wave height has a linear relationship with the wave height where the wave transformation starts.

\[ H_t = K_R K_S H_{ref} \]  \hspace{1cm} (2.1)

Where
\( H_t \) = transformed wave height at destination
\( K_R \) = refraction coefficient
\( K_S \) = shoaling coefficient
\( H_{ref} \) = wave height at the offshore reference depth or the nearshore reference line

The refraction coefficient \( K_R \) is a function of the starting angle of the ray and the angle of breaker.

\[ K_R = \frac{\cos \beta_r}{\sqrt{\cos \beta_t}} \]  \hspace{1cm} (2.2)

where, \( \beta_r \) and \( \beta_t \) are the angle between the wave ray and the bathymetry contour of the starting point and the destination respectively.
The shoaling coefficient $K_S$ is a function of the wave period, the depth at starting point, and the destination.

$$K_S = \sqrt{\frac{C_{gr}}{C_{gt}}}$$  \hspace{1cm} (2.3)

where, $C_{gr}$ and $C_{gt}$ are the group wave celerity of the starting point and the destination respectively.

$$C_g = nC$$  \hspace{1cm} (2.4)

where, $n$ is the wave number and $C$ is the wave phase speed. They are given by the following equation.

$$n = \frac{1}{2} \left[ 1 + \frac{2kd}{\sinh(2kd)} \right], \quad C = L / T$$  \hspace{1cm} (2.5)

The wave length $L$ can be computed through the following dispersion relation.

$$\frac{\omega^2 d}{g} = kd \tanh kd$$  \hspace{1cm} (2.6)

where, $d$ is the water depth at the corresponding point, and $k$ is the wave number, equal to $2\pi/L$.

In addition, the wave angle in the equation involved with refraction coefficient can be obtained through the following Snell’s Law.

$$\frac{\sin \beta_i}{C_i} = \frac{\sin \beta_r}{C_r} = \text{constant}$$  \hspace{1cm} (2.7)

Finally, the wave height can be transformed from a reference point to an arbitrary location, which can be either a deep-water location or nearshore location.
2.2 Wave runup process

The wave runup is a complex wave propagation process. When waves are approaching a coast, the majority of energy is dissipated across the surf zone by wave breaking. However, a small portion of the energy is converted into potential energy in the form of runup on the foreshore of the beach (Stockdon, 2006). According to the description of the processes, wave runup is defined as the maximum elevation of wave uprush above still-water level. Wave uprush consists of two components: superelevation ($\eta$) of the mean water level due to wave action (setup) and fluctuations about that mean (swash). The upper limit of runup is an important parameter for determining the active portion of the beach profile. From a statistical point of view, the maximum height it can reach is defined as the $R_{\text{max}}$. If only 2% of wave can run up to or higher than the height, then it is defined as $R_{2\%}$ or $R_2$. Several field experiments have conducted as to investigate the factors that determine the wave runup. Rathbun, Cox and Edge (1998) have found that the wave runup is a function of deep-water wave significant wave height and surf similarity parameter. Stockdon (2006) has proved that the wave runup is a function of deep-water wave parameters and the beach steepness. As a result, he quantifies the wave runup based on the 10 field experiments as below.

$$R_2 = 1.1 \left( 0.35 \beta_f \left( H_0 L_0 \right)^{1/2} + \frac{\left[ H_0 L_0 (0.563 \beta_f^3 + 0.004) \right]^{1/2}}{2} \right)$$

(2.8)

where, beach steepness $\beta_f$ is the foreshore slope. $H_0$ and $L_0$ are deep-water wave height, and deep-water wave length respectively.

2.3 Statistical models

Coastal change is a complicated process, for it is result of a multiple factors’ interaction. In order to extract out the shoreline change pattern and change rate, time series models and linear models have applied to the shoreline data, respectively.
2.3.1 Time series analysis

(1) Measures of temporal dependency

In the time series models, there are two important functions that measures the linear dependence between two points on the same series observed at different times. One is the Autocorrelation Function (ACF), and the other is the Partial Autocorrelation Function (PACF).

Before an ACF or PACF can be formulated, it is essential to know that the definition of autocovariance function, which is defined as the second moment product.

\[ \gamma(h) = E[(x_{t+h} - \mu)(x_t - \mu)] \] \hspace{1cm} (2.9)

where, \( \mu \) is denoted as the mean and \( h \) is denoted as the lag in time.

Very smooth series exhibit autocovariance functions that stay large even when the lags are big, whereas choppy series tend to have autocovariance functions that are nearly zero for large separations.

Based on the definition of autocovariance function, the ACF of a stationary process is defined as

\[ \rho(h) = \frac{\gamma(t+h,t)}{\sqrt{\gamma(t+h,t+h)\gamma(t,t)}} = \frac{\gamma(h)}{\gamma(0)} \] \hspace{1cm} (2.10)

The ACF measures the linear predictability of the time series at time \( t \), using only the value \( x_{t+h} \). The ACF is a rough measure of the ability to forecast the series, and can be used for the determination of MA(q) model.

The PACF of a stationary process \( x_t \) denoted is defined as \( \phi_{hh} \), for \( h=1, 2, \ldots, \) is

\[ \phi_{11} = corr(x_1, x_0) = \rho(1) \] \hspace{1cm} (2.11)

and

\[ \phi_{hh} = corr(x_h - x_{h-1}', x_0 - x_{0-1}'), h \geq 2 \] \hspace{1cm} (2.12)

where, \( x_{h-1}' \) is denoted as the regression of \( x_h \) on \( \{x_{h-1}, x_{h-2}, \ldots, x_1\} \), which we write as
\[ x_n^{h-1} = \beta_1 x_{n-1} + \beta_2 x_{n-2} + \ldots + \beta_{h-1} x_1 \] (2.13)

Both \((x_n - x_n^{h-1})\) and \((x_0 - x_0^{h-1})\) are uncorrelated with \(\{x_1, x_2, \ldots, x_{h-1}\}\). By stationary, the PACF, \(\phi_{nh}\), is the correlation between \(x_t\) and \(x_{t-h}\) with the linear dependence of \(\{x_{t-1}, x_{t-2}, \ldots, x_{t-(h-1)}\}\), on each, removed. The PACF is used for the determination of AR(p) model.

(2) ARMA model

The Autoregressive Moving Average ARMA \((p, q)\) model includes two terms, i.e., AR \((p)\), an autoregressive model, and MA \((q)\), and Moving Average model. The parameter \(p\) refers to the order in an autoregressive model, and the parameter \(q\) refers to the order in a moving average model. Though the ARMA model cannot be used to estimate the “slope” as opposed to that in the linear regression model, the details of change pattern for the sampled data can be better captured and characterized.

ARMA \((p, q)\) model can be applied to fitting the stationary time series data (at least weakly stationary), and it has the following structure.

\[ x_t = \phi_1 x_{t-1} + L + \phi_p x_{t-p} + w_t + \theta_q w_{t-q} + \ldots \] (2.14)

With \(\phi_p \neq 0\), \(\theta_q \neq 0\), and \(\sigma_w^2 > 0\). The parameter \(p\) and \(q\) are called the autoregressive and the moving average orders, respectively. If \(x_t\) has a nonzero mean \(\mu\), we set \(\alpha = \mu(1-\phi_1-L-\phi_p)\) and write the model as

\[ x_t = \alpha + \phi_1 x_{t-1} + L + \phi_p x_{t-p} + w_t + \theta_q w_{t-q} + \ldots \] (2.15)

Generally, we assume \(\{w_t: t = 0, \pm 1, \pm 2, K\}\) has a Gaussian white noise distribution.

The two parameters, \(p\) and \(q\) needs to be specified by computing ACF, PACF, or AIC (Akaike’s Information Criterion), before other parameters in this model can be estimated. AR(p) is characterized by a PACF, i.e., nonzero at lag \(p\), and zero for lags larger than \(p\). MA(q) is characterized by an ACF that is, nonzero at lag \(q\), and zero for lags larger than \(q\).
For anything else, try ARMA(p,q) with p>0 and q>0, and select the best objective model with the minimum AIC.

(3) Periodogram analysis

The periodogram analysis is a way to discover the periodic components of a time series. The scaled periodogram is expressed as below.

\[
P(j/n) = \left( \frac{2}{n} \sum_{t=1}^{n} x_t \cos(2\pi tj/n) \right)^2 + \left( \frac{2}{n} \sum_{t=1}^{n} x_t \sin(2\pi tj/n) \right)^2
\]  

It represents the measure of the squared correlation of the data with sinusoids oscillating at a frequency of \( \omega_j = j/n \), or \( j \) cycles in \( n \) points. Therefore, for any give stationary time series data, if the periodic components exist, the estimated periodogram will become significant large. Then, the periodicity can be found for the time series data.

2.3.2 Linear models

(1) Guass-Markov model

The Guass-Markov Model takes the form

\[
y = Xb + e
\]  

Where \( y \) is the \( (N \times 1) \) vector of observed responses, and \( X \) is the \( (N \times p) \) known design matrix. The coefficient \( b \) is to be estimated and usually named as the linear “rate” or slope. The main feature of the Guass-Markov model has the following assumption on the error \( e \):

\[
E(e) = 0 \text{ and } Cov(e) = \sigma^2 I_N
\]  

That is, the errors in the model have zero mean, constant variance, and are uncorrelated. An alternative view of the Gauss-Markov Model does not employ the error vector \( e \):

\[
E(y) = Xb, Cov(y) = \sigma^2 I_N
\]
Under this model assumption, the OLS (Ordinary Least Square) estimator $\lambda^T \tilde{b}_{OLS}$ is the best linear unbiased estimator (BLUE) for $\lambda^T b$, where $\tilde{b}_{OLS}$ solves the normal equations $X^T X \tilde{b} = X^T y$, and equals to $(X^T X)^{-1} X^T y$.

The assumptions in the Guass-Markov model are easily acceptable for many practical problems. However, when the residuals of the fitted data have a special pattern which is not a scaled identity matrix, say, the sampled data have some spatial or temporal correlation, the assumption cannot be satisfied and the use of Guass-Markov model is not feasible any more. As a result, a more complex derived model based Guass-Markov model will be considered.

(2) Aitken model

The Aitken Model is a slight extension of the Guass-Markov Model in that only different moment assumptions are made on the errors. The Aitken Model takes the form $y = Xb + e$, where $E(e) = 0$ and $Cov(e) = \sigma^2 V$. The matrix $V$ is an unknown positive definite matrix, but not necessarily an identity matrix. Under the assumption of Aitken Model, the linear squares estimator $\lambda^T \tilde{b}_{OLS}$ may not longer be the BLUE (Best Linear Unbiased Estimator) for $\lambda^T b$. A generalized least squares (GLS) estimator of $\lambda^T \tilde{b}_{GLS}$ is the BLUE for $\lambda^T b$. To get the GLS estimator by given the form $y = Xb + e$, the Aitken equation can be reformed as $X^T V^{-1} X \tilde{b} = X^T V^{-1} y$. $\tilde{b}_{GLS}$ solves the normal equations $X^T V^{-1} X \tilde{b} = X^T V^{-1} y$, and equals to $(X^T V^{-1} X)^{-1} X^T V^{-1} y$. Since the covariance matrix $V$ appears in $\tilde{b}_{GLS}$ term, the magnitude of $\tilde{b}_{GLS}$ could be affected by the structure of residual.

(3) Autoregressive Error Model

The Autoregressive Error Model (AEM) is a special Aitken model, in which the covariance structure of the residual is estimated by the AR model. It is used to estimate and forecast linear regression models for time series data when the residuals are autocorrelated or
heteroscedastic. Given the form of Aitken model, the regression model with autocorrelated disturbances is as follows:

\[ y_t = X_t \beta + \nu_t \]  
\[ \nu_t = \epsilon_t - \phi_1 \nu_{t-1} - \phi_p \nu_{t-p}, \epsilon_t \sim N(0, \sigma^2) \]

In this equation, \( y_t \) is the dependent variable, and \( X_t \) are the explanatory variables. \( \beta \) is a column vector of structural parameters, and \( \epsilon_t \) is normally and independently distributed with a mean of 0 and a variance of \( \sigma^2 \). This model is used to estimate the slope of \( X \), when the residual term has an AR structure.

### 2.3.3 Multivariate analysis

Multivariate analysis is useful when the observations are involved with more than one statistical variable. It can be used for structural simplification, grouping, investigation of dependence among variables, and prediction. In this study, the data reduction and clustering is of our focus.

(1) Principal Component Analysis (PCA)

A PCA is concerned with explaining the variance-covariance structure of a set of variables through a few linear combinations of these variables. The principal components are defined as those linear combinations which have maximum variance.

Suppose there is a matrix \( x = [x_1, x_2, ..., x_p] \), in which \( x_i, i = 1, 2, ..., n \) are column vectors and these column vectors are observations for each variable. Then the covariance matrix for all pairs of variables can be written as \( S = \{Cor(x_i, x_j)\}, i, j = 1, 2, ..., p \), which is a \( p \times p \) covariance matrix with eigenvalue-eigenvector pairs \( (\hat{\lambda}_1, \hat{\epsilon}_1), (\hat{\lambda}_2, \hat{\epsilon}_2), ..., (\hat{\lambda}_p, \hat{\epsilon}_p) \). Finally, the \( i \)th principal components is given by \( \hat{y}_i = \hat{\epsilon}_i^T x, i = 1, 2, ..., p \).

where, \( \hat{\lambda}_1 \geq \hat{\lambda}_2 \geq L \geq \hat{\lambda}_p \geq 0 \) and \( x \) is any observation on the variables \( X_1, X_2, ..., X_p \). Also,
sample variance $S(\hat{y}_k) = \hat{\lambda}_k, k = 1, 2, ..., p$

sample covariance $Cor(\hat{y}_i, \hat{y}_k) = 0, i \neq k$

In addition, the total variance $= \sum_{i=1}^{p} s_{ii} = \hat{\lambda}_1 + \hat{\lambda}_2 + \cdots + \hat{\lambda}_p$, and the proportion of total population variance due to $k$th principal component $= \hat{\lambda}_k / \sum_{i=1}^{p} s_{ii}$. Moreover, each component of coefficient vector $\hat{e}_i = [\hat{e}_{i1}, \hat{e}_{i2}, ..., \hat{e}_{ip}]$ also merits inspection. The magnitude of $\hat{e}_k$ measures the importance of the $k$th variable to the $i$th principal component.

(2) Clustering analysis

Searching the data for a structure of “natural” grouping is an important exploratory technique. Clustering can provide an informal means for assessing dimensionality, identifying similarity, and suggesting interesting hypothesis concerning relationships. Clustering analysis is a primitive technique in that no assumptions are made concerning the number of groups or the group structure. It is done on basis of similarities of distances, and the inputs are the similarity measures from which similarities can be computed.

The hierarchical clustering method has been widely used for grouping objectives. Agglomerative hierarchical methods starts with individual objects, and the most similar objects are first grouped. Then, these initial groups are merged according to their similarities. Finally, as the similarity decreases, all subgroups are fused into a single cluster.
3 Study area and data collection

3.1 Study area

Oregon Inlet is located at the North Carolina Outer Banks between Bodie Island to the North and Pea Island to the south (Figure I-3.1). Our study area extends from the north end of Pea Island for a distance of approximately 6 miles to the south. Oregon Inlet is a naturally migrating inlet that over a period of 126 years has migrated south at an average rate of 23 m/yr and receded to the west at an average rate of 5 m/yr (Overton et al., 2004). In 1989, a terminal groin was built to stabilize the north end of Pea Island and to protect the Bonner Bridge. As to determine if the construction of the terminal groin has been increasing the rate of erosion on the downdrift side, aerial photography is taken every two months and ground surveys are conducted at several transect locations twice a year since then. Result show that no significant erosion above background rates have occurred within the first 5 miles south of Oregon Inlet (e.g., Overton and Fisher, 2004).

Figure I-3.2 shows ground survey transects with transect number and the envelope of the most landward and seaward shorelines from October 1989 to April 2009, overlaid on the orthophoto (October 8, 2009). There are 33 survey transects used in this study and they are listed from the north to south in Table I-3.1 and plotted in Figure I-3.2 below. It is clear to see that the region at northward side of the transect #16+00 is most dynamic, but that at southward side of the transect #16+00 has less changes. The historical shoreline data indicates that the averaged erosion rates for the two parts above are about 100 ft/yr and 20 ft/yr respectively, which indicates a strong spatial variation of shoreline change exists in this region. The purpose of chosen Oregon Inlet as the study area, is due to the availability of time series shoreline data, wave data as well as tide data, and also to show how the shoreline change pattern varies spatially as a matter of geomorphologic characteristics change and wave climate change.
Figure I-3.1: Study area: a. Location; b. 3-D overview.
Figure I-3.2: Study area with the most landward and seaward shoreline from 1989 to 2009.
Table I-3.1: Survey transect number with corresponding order number.

<table>
<thead>
<tr>
<th>Order</th>
<th>Transect No.</th>
<th>Distance (mile)</th>
<th>Order</th>
<th>Transect No.</th>
<th>Distance (mile)</th>
<th>Order</th>
<th>Transect No.</th>
<th>Distance (mile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11+00</td>
<td>0.42</td>
<td>12</td>
<td>106+00-A</td>
<td>1.41</td>
<td>23</td>
<td>116+00</td>
<td>3.29</td>
</tr>
<tr>
<td>2</td>
<td>16+00</td>
<td>0.51</td>
<td>13</td>
<td>107+00</td>
<td>1.50</td>
<td>24</td>
<td>117+00</td>
<td>3.49</td>
</tr>
<tr>
<td>3</td>
<td>21+00</td>
<td>0.61</td>
<td>14</td>
<td>107+00-A</td>
<td>1.60</td>
<td>25</td>
<td>118+00</td>
<td>3.69</td>
</tr>
<tr>
<td>4</td>
<td>25+91</td>
<td>0.70</td>
<td>15</td>
<td>108+00</td>
<td>1.70</td>
<td>26</td>
<td>119+00-A</td>
<td>4.00</td>
</tr>
<tr>
<td>5</td>
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<td>0.78</td>
<td>16</td>
<td>109+00</td>
<td>1.88</td>
<td>27</td>
<td>121+00</td>
<td>4.32</td>
</tr>
<tr>
<td>6</td>
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<td>0.87</td>
<td>17</td>
<td>110+00</td>
<td>2.07</td>
<td>28</td>
<td>122+00-A</td>
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<tr>
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<td>18</td>
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<td>31</td>
<td>127+00</td>
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</tr>
<tr>
<td>10</td>
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<td>1.23</td>
<td>21</td>
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<td>2.86</td>
<td>32</td>
<td>130+00</td>
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<tr>
<td>11</td>
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<td>1.32</td>
<td>22</td>
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<td>3.07</td>
<td>33</td>
<td>133+00</td>
<td>6.87</td>
</tr>
</tbody>
</table>

Note: the distance is referenced to the tip of the Terminal Groin of Oregon Inlet.

### 3.2 Data collection

The data used in this study covers the period from October 1989 to April 2009. The survey data is collected every six months by NCDOT (North Carolina Department of Transportation). Additional data used is downloaded from public domain sources and data collection agencies, such as tide station, wave gauge stations.

1. Flight time data

   The flight time associated with the shoreline is used to determine both of the wave and tide conditions. The most flights were conducted between 10am and 2pm on a survey day. For the unavailable flight time, we use 12:00pm as the default time to look up the correct wave and tide conditions.

2. Tide data

   The tide data used in this study was collected from the NOAA station at Duck, NC (#8651370), which is located northward of Oregon Inlet. The tide data was sampled at a time
interval of 6 min. All tide data used in this study was based on the time when the aerial photos were taken, based on MTL (Mean Tidal Level) datum in meter.

(3) Wave data

The wave data used in this study comes from two sources, which are the WIS (Wave Information Studies) data and wave gauge data, including significant wave height, peak wave period and averaged wave direction, as well as the wind speed and direction, with a constant sample rate of one hour. The WIS data is generated by numerical simulation of past wind and wave conditions, a process called hindcast. Due to the availability of WIS data, only the time period from 1989 to 1999 at Station #222 was used in this study to characterize the wave conditions, which is located at Lat/Lon of 35.92/-75.42 with a depth of 19 m. In addition to WIS data, the wave gauge data was used as a backup source and was retrieved from NOAA buoy station #44014 for the period from 2000 to 2009, for the wave gauge data does not have a good availability before 2000. This station is located at Virginia Beach in VA (36°36'40" N, 74°50'11" W) with a water depth of 47.5 m. The wave data from two sources were collected based on the time when the actual aerial photos were taken.

(4) Shoreline data

The shoreline data are retrieved from the combination of T-sheet and aerial photos in means of wet/dry shoreline, collected by NCDOT. It delineates the contact of land and the water and reflects the position of water/land contact at that moment. The shoreline data used in this study includes the historical shoreline GIS vector data from October 1989 to April 2009 in April and October for each year, which are totally 40 datasets.

(5) Beach profile data

The ground surveys of beach profile were conducted twice a year since 1989, which were in April and October. The locations of ground surveys were shown by survey transect in Figure I-3.2. This profile describes the variation of elevation along a survey transect cross-shore, and can be used to provide topography information, such as beach slope. Generally, the dates
of beach surveys are approximately consistent with the airplane flight dates, with a few exceptions (Table I-3.2). It is assumed that the differences between the two dates will not result in topographic changes.

Table I-3.2 Comparison between beach survey dates and airplane flight dates

<table>
<thead>
<tr>
<th>Flight date</th>
<th>Survey date</th>
<th>Flight date</th>
<th>Survey date</th>
</tr>
</thead>
</table>

Overall, all the spatial data above have been referenced to State Plane 3200 horizontally and NAVD 88 vertically.
4 Methods

With the description and definition of shoreline above, the elevation of the wet/dry shoreline can be modeled as a function of the “real” shoreline level, tide level and wave runup level. As a result, the “real” shoreline can be exposed by removing the tide and wave runup factors. Finally, the rectified shoreline can reflect the geomorphology changes alongshore caused by the sediment transport process, but not due to wave or tide level changes.

4.1 Shoreline rectification

Figure 4-1 below provides a flow chart of the procedure to remove the horizontal displacement of the shoreline due to the presence of waves and tides at the time of the aerial photography. In order to estimate the “real” shoreline, the tide and wave effects should be removed. The tide level can be easily obtained from the records at tide stations, while the wave runup can be well estimated through the techniques of runup computation by knowing the foreshore slope and deep-water wave conditions. The total vertical shift from the “real” shoreline to the wet/dry shoreline can be assumed to be the summation of tide level (MTL) and wave runup. Finally, the “real” shoreline can be estimated by eliminating the effects of the tide level and wave runup. This methodology was applied to all transects overt the 20-year study period.

Figure I-4.1: Flow chart of wave runup estimation and shoreline rectification.
4.1.1 Tide estimation

The tide level is not a constant over time, but fluctuates from time to time due to the rotation of the earth. Since the wet/dry shoreline was digitized based on the orthophotos, we use the previous high tide level on the date before the orthophoto was taken, which is based on the Mean Tidal Level (MTL).

4.1.2 Wave runup computation

Recall the runup equation (2.8), three variables need to be obtained before it can be estimated, which are the foreshore slope, deep-water wave height \( H_0 \) and wave length \( L_0 \). The foreshore slope will be extracted from the beach profile data, while the deep-water wave height and wave length will be computed via linear wave theory based on the data provided by the wave gauges.

1) Foreshore slope

The beach profile extends from NC 12 to approximately MLW (Mean Low Water). The foreshore slope \( \beta_f \) was computed based on the end section of the beach profile, which is approximately between MHW and MLW. The elevation were extracted and the foreshore slope was computed automatically at 33 survey transects for 40 datasets from October 1989 to April 2009.

2) Deep-water wave conditions

The deepwater wave height \( H_0 \) was computed from the collected wave data via linear wave theory, but only considered the shoaling (dispersion relation) and refraction (Snell’s Law) processes, i.e., the deep-water wave height \( H_0 \) is a function of refraction coefficient \( K_R \), shoaling coefficient \( K_S \), and wave height at reference points \( H_{ref} \).

\[
H_0 = K_R K_S H_{ref}
\]  

(4.1)
The deep water wave length $L_0$ is formulated by the equation $L_0 = gT^2 / 2\pi$, which is only a function of peak wave period. Both computations of wave parameters are based on wave conditions at the flight time on the day.

(3) Wave runup estimation

Given the foreshore slope $\beta_f$, deep-water wave height $H_0$ and wave length $L_0$, the 2% exceedence wave runup was computed for 33 transects of total 40 time points based on the following equation (Stockdon, 2006).

$$R_z = 1.1 \left( 0.35 \beta_f (H_0L_0)^{1/2} + \frac{[H_0L_0(0.563\beta_f^2 + 0.004)]^{1/2}}{2} \right)$$ (4.2)

It is noticed that the 2% exceedence wave runup is a monotone increasing function of $\beta_f$, $H_0$ and $L_0$, which means that higher wave height, longer wave length or steeper foreshore slope will elevate the wave runup and cause erosion to the beach region. Finally, the estimated wave runup will be used as the wave effect on the shoreline rectification.

4.1.3 Wet/dry shoreline rectification

The biased term (wave runup and tide level) was added to the wet/dry shorelines as to create new shorelines. It is assumed that the rectified shoreline has approximately the same metric as the “real” shoreline. To estimate the effects due to wave and tide, first, the total vertical shoreline shift was computed, which is the summation of wave runup and tide elevation (MTL). This effect may have caused the wet/dry shoreline a little bit upward above its actual level when it was calm. Since only the horizontal position of the shoreline is our focus, the estimated vertical shift in previous step was converted into the corresponding horizontal shift based on the foreshore slope. A positive horizontal shift indicates the rectified shoreline should move oceanward horizontally, while a negative horizontal shift indicates the rectified shoreline should move landward horizontally. The horizontal position of the final rectified shoreline is the original position minus the estimated horizontal shift.
Finally, the computed biased term needs to be applied to all wet/dry shoreline, as to get the rectified shoreline data. Thus, Linear Referencing (LR) was applied to achieve this purpose. LR is a technique of recording geographic locations by using relative positions along a measured linear feature. In this study, we firstly define the origin at each survey transect and compute the relative location of the original shoreline to the origin. Then, apply LR technique to rectifying shoreline position along each survey transect based on the computed horizontal shoreline shift. Last, convert the relative shoreline position into ordinary position in original coordinate system. As a result, the rectified shorelines were created and wave/tide effects have been removed.

4.2 Shoreline change analysis

Before the shoreline change analysis can be performed, all the shoreline positions are recorded as distances measured from a fixed reference line offshore. In this case, an increase in distance indicates erosion and a decrease in distance indicates accretion. To characterize the shoreline change, both shoreline change pattern and change rate are considered in the analysis.

Shoreline change pattern can be captured by a few time series models, such as ARMA, periodogram analysis and PCA, while the shoreline change rate can be well estimated by the Aitken method if the choice of covariance of the residual is appropriate. The ACF/PACF can be used to characterize the structure of the residual and help to identify the most appropriate ARMA model. Based on the ARMA model, the parameterized Aitken model was used to estimate the shoreline change rate while considering the temporal correlation exists. Finally, the estimated rate by Aitken model (AEM) was compared with that by the OLS method to see the significant differences. Figure I-4.2 below shows the procedure for the shoreline change analysis process.
4.2.1 Shoreline change pattern

(1) Analysis of temporal dependency

Shoreline positions were firstly sampled at the predefined survey transects in the time series records. In order to see the structure of data residuals, the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) were computed and plotted after the data trend was removed. The pattern of ACF and PACF will show how the shoreline positions were temporally correlated.
(2) Parameterization of ARMA model

The ARMA model is usually used to model and quantify the temporal correlation existing in the residuals, though its major purpose is for forecasting data. Before an ARMA model can be applied to any time series data, its AR and MA components must be determined. The most commonly used method is to compute the ACF/PACF to see whether it tails off or cuts off when the lag increases. The preliminary results suggest that ACF for all transect tails off with sinuous or cosine pattern, while most of PACF cuts off after lag 1 or lag 2. As a result, AR(2) should be the most appropriate model to capture the covariance structure of the residuals.

(3) Shoreline change periodicity

Periodogram analysis is used to identify the periodicity existing in the data residuals. It is necessary to perform the periodogram analysis, if the estimated ACF has shown a sinuous or cosine pattern. The temporal trend has to be removed before the periodogram analysis was performed. The spectral power was computed for each transect location and the frequencies with significant spectral power are the associated periodicities for the corresponding time series shoreline data.

(4) PCA analysis and hierarchical clustering

Principal Component Analysis is also referred to as EOF (Empirical Orthogonal Function) analysis, and has become a common tool in analyzing and visualizing coastal data sets that vary over large spatial and temporal scales (Miller and Dean, 2007a; Hansen and Barnard, 2010). In this study, PCA was applied to the shoreline change data, which is sorted by transect in row, and by time in column. Times and locations (transects) are taken as variables respectively, as to perform PCA for each case. The outputs are the eigenvalues and associated eigenvectors. The scree plot, eigenvaues vs. index, was used to visually illustrate the percentage of total variance explained by each principal component. The eigenvectors are used to explain how much weight was put on each raw variable. As a result, the element magnitude of the eigenvectors of the first a few principal components can reflect the variation of shoreline change in time and space.
As to capture the shoreline change pattern, the agglomerative hierarchical clustering technique was applied to the shoreline change data. The BIC (Bayesian Information Criterion) was computed before the clustering, to decide the number of categories. The maximum BIC determines the best categories and clustering model for the data. Finally, the average linkage method was used to compute the distance between clusters, and the dendrogram was plotted as to see the structure of the hierarchical clusters.

4.2.2 Modeling shoreline change rate

In order to estimate the shoreline change rate, the Autoregressive Error Model (AEM) was built by specifying the covariance of residuals as an AR(2) process based on the GLS method. Since the wave and tide effects have been removed from the shoreline data, we consider the shoreline position is a function of time only, assuming storms and human activities as random events. Residuals and change rate will be obtained after the model is fitted. Finally, the estimated slope in this model represents the shoreline change rate, and the estimated weight on each AR term quantify how much the current shoreline position is affected by its previous position.
5 Result

5.1 Wave runup and shoreline shift

The averaged wave runup over transects for each year is shown below (Figure I-5.1). It is clear to conclude that almost all the wave runups are between 0.2 m and 2.5 m, while most of them are below 1.5 m, with the exception in October, 1998, which is due to both higher $H_0$ and longer wave period on photo taken date. In addition, the spatial variation of wave runup over difference transects exists due to the spatial variation of foreshore slope.

Finally, the estimated horizontal shoreline shifts based on the wave runup and tide level were applied to the rectification of the shorelines. The results suggest the averaged horizontal shift of shoreline over transects for each year is between 5 m and 10 m with a few exceptions, such as October 1999, in which the averaged horizontal shift is -7.42 m, for the tide level during the flight time is relative low (-0.46 m).

![Figure I-5.1: Estimation of averaged wave runup over transects for each year.](image-url)
5.2 Shoreline change pattern

(1) ACF of shoreline data residuals

The ACF plots below (Figure I-5.2) have shown that the residuals of shoreline data are not randomly distributed, but have special distribution patterns, which suggest temporal dependencies exist in the time series shoreline data at each survey transects. From the transect #5 to #15, the ACF plots have shown a sinuous or cosine pattern of the residual distribution, indicating periodicity of shoreline changes exists from the Oregon Inlet to its south at transect #20. From transect #20 to #33, the ACF does not show a special pattern of the residuals, which means that the temporal correlation from the transect #20 to its south is not significant but may still exist in the data. After all, more detailed temporal properties of the data need to be extracted out by the following time series models.
Figure I-5.2: ACF/PACF of shoreline data residuals at transect basis.
(2) Shoreline change periodogram

The periodogram below (Figure I-5.3) has shown the spatial differences from transect to transect. A significant frequency at 0.1 to 0.4 from transect #5 to #15 has shown a periodicity of 1.25 to 5 years of shoreline change. When it goes from the transect #20 to #33, multiple peaks exist in the spectral graph and moves to higher frequencies, which suggests the shoreline changes southward do not have significant periodicity.
Figure I-5.3: Periodogram analysis of time series shoreline positions on transect basis.
Periodogram at Transet #5

Periodogram at Transet #10

Periodogram at Transet #15
(3) Principal components of shoreline changes

a. Taking transects as variables

Figure I-5.4 shows the plot of eigenvalues, named as the scree plot, for which the PCA was performed by taking the locations as multiple variables. The scree plot suggests that the first principal component can explain the most of the variance for all years. The computation also shows that 50.9% of the total variance can be explained by the first principal component, and 75.3% of the total variance can be explained by the first four principal components.

![Figure I-5.4: Scree plot for the PCA on transects of shoreline change data.](image)

Figure I-5.5 has clearly shown that the shoreline changes oscillate intensively for the first 20 transects (about 2.65 miles from the Oregon Inlet), relative to the last 13 transects, based on the eigenvectors of the first four principal components. By looking at only the eigenvector of the first principal component, negative values indicate that the shoreline accretion dominated the whole shoreline evolution process during the past 20 years, while the first 20 transects,
which are about 2.65 miles from the Oregon Inlet, had more accretion as compared with the last 13 transects.

In addition to the eigen-vectors of principal components, the first principal component was also plotted as below (Figure I-5.6), which can explain 50.9% of the total variance. Four extraordinary points were marked due to some special events happened associated with them. By looking at the storm historical records, Hurricane Emily, Dennis, and Isabel, occurred in September 1993, September 1999 and September 2003 respectively. These storm events are the best indicators which can be used to explain the great shoreline recession in those years (event 1, 2 and 3, positive value means shoreline erosion). Moreover, event 4 has shown a shoreline accretion in 2004 (negative value means shoreline accretion). By looking at beach projects, nourishment project has been implemented and a huge amount of sand (1.03 million cubic yard) was placed in October 2004, which can well explain why a big shoreline accretion is detected in between 2003 and 2004.

Figure I-5.5: The eigenvectors of the first four components versus distant alongshore.
Figure I-5.6: The geographic locations of the beach nourishment projects.

Figure I-5.7 below is showing the major beach nourishment projects implemented during the past 20 years. The horizontal lines represent the geographic region covered by the beach nourishments, measured by distance from the Terminal Groin of Oregon Inlet. The locations of beach nourishment projects are very consistent with the spatial principal components, i.e., the locations which have larger weights are the places where the beach nourishment was conducted. As a result, the beach nourishment project is one of the major factors causing the intensive oscillation of shoreline changes.
b. Taking times as variables

Figure I-5.8 shows the scree plot, for which the PCA was performed by taking times as multiple variables. It is clear to see that the first four principal components explain the most of the total variance, though the first principal component does not significantly explain the most of the total variance. The computation shows that 20.7% of the total variance can be explained by the first principal component, and 59.3% of the total variance can be explained by the first four principal components.
Figure I-5.8: Scree plot for the PCA on times of shoreline change data.

Figure I-5.9 shows the eigenvectors of the first four components versus year. The magnitudes of the eigenvectors elements suggest that the variations of shoreline changes are less dependent on the period from 1994 to 2002, which means that the shoreline changes were relatively small during the period from 1994 to 2002, while that is higher before 1994 and after 2002. In addition, the shoreline changes after year 2002 were a little bit higher than that before year 1994.
Figure I-5.9: The eigenvectors of the first four components versus year.

Figure I-5.10 is showing the historical records of the beach nourishment projects, as well as big storms. It suggests the volume of disposal sand is relative small during the period from 1994 to 2002, but relative high during the period before 1994 and after 2002. This result is also consistent with the temporal principal components, i.e., the years which have less weights in the principal components are the years when smaller amount of sand was nourished. Therefore, the beach nourishment projects may be the major factors causing the shoreline changes. In addition, the dates of a few big storm events are also consistent with some higher oscillations of the eigenvectors of the principal components, especially for the year 2003. As result, the storm event is probably another important factor causing the shoreline changes.
Figure I-5.10: The history records of the beach nourishment projects and storms.

(4) Shoreline changes clustering

By running model selection function (Mclust) for hierarchical clustering, we get the maximum BIC of -11699.14, which suggests “ellipsoidal, equal volume, shape, and orientation” model with 6 clusters. As a result, we divide all the shoreline change styles based transects into 6 categories. Figure I-5.11 shows the dendrogram of the cluster, which suggests that last 27 transects have similar shoreline change patterns.
5.3 Shoreline change rate

The Figure I-5.12 below shows the shoreline change rate for each transect during the period from 1989 to 2009, in which positive rate refers to erosion, and negative rate refers to accretion. The spatial variation of shoreline change rate exposed different change patterns affected by the geomorphologic properties from the Oregon Inlet to its south. It is clear to see that the general spatial trend of shoreline change rate are quite similar derived by both OLS and AEM methods. From the Oregon Inlet to its south, the shoreline change rate increases till the transect #12, and then decreases till transect #15. From transect #16 to #23, shoreline change rate remain approximately the same. From transect #24 to #33, the shoreline change rate goes up and down. Since the positive rate means erosion and negative rate means accretion, the shoreline change pattern has a general trend of increasing erosion when it goes from the Oregon Inlet to its south. However, the estimated shoreline change rate by AEM is almost always below that by the OLS regression method, which means that OLS regression method has over estimated the shoreline erosion rate, by ignoring the temporal correlation in the shoreline data. As a result, to simply apply the OLS method to the estimation of linear rate will mislead to the wrong change pattern of the shorelines.
Figure I-5.12: The comparison of shoreline change rates between the OLS and AEM methods.

The Figure I-5.13 below shows the estimate parameters for AR terms with their associated p-values. Almost all the factors for the AR term are negative, which means the residual terms of current shoreline positions are always decreased by the previous ones, i.e., those unknown factors cause accretion to the shorelines. By looking at the p-values, the significant AR(1) process appears between the transect #5 to #10 and #20 to #25, while the significant AR(2) only appears between transect #10 to #15. Therefore, those unknown factors affected shoreline position mostly at a lag of a half year.
Figure I-5.13: The estimated parameters for the AR terms and their associated p-values.
6 Discussion

In this study, the shoreline change pattern and rate were analyzed by considering both wave/tide effects and statistical models. The wave runup or tide fluctuation may cause an instant water level shift, which results in wet/dry shoreline shift consequently. The statistical models have been applied to the rectified shoreline data, in order to capture the shoreline change pattern and rate, and finally can be used for prediction.

(1) Wave / tide effects

To remove the wave/tide effects, the wet/dry shoreline were firstly rectified by computing the wave runup and tide level, in which the waves result in water level raise due to wave runup, while the tide causes a water level raise directly. It is assumed that the rectified shoreline is more closed to the “actual” shoreline due to the removal of wave/tide effect. However, the estimated wave runup may not exactly reflect the actual wave runup, which results in the wet line alongshore.

(2) Capturing shoreline variation

The PCA has extracted the structure of the shoreline change variations. In the means of both spatial and temporal view, the special pattern of shoreline change variations was exposed distinctly and well explained by the beach nourishment activity and the storm events qualitatively. However, the magnitude of shoreline change variations may need to be further discussed by correlating with the beach nourishment volume and the storm index, in order to address how the beach nourishment and storm events change the shoreline quantitatively.

(3) Estimation of shoreline change rate

OLS regression method is based on several statistical assumptions. One key assumption is that the residuals are independent of each other. However, the estimation of ACF / PACF reveals that strong temporal dependency exists in the shoreline data. As a result, the violation of the independent residual assumption has two important consequences for the OLS regression method. First, the statistical tests of the significance of the parameters and the
confidence intervals for the predicted values are not correct. Second, the estimations of the regression coefficients are not as efficient as they would be if temporal dependency is taken into account. Finally, since the residuals of OLS regressions are not independent, the additional information in the residuals, temporal dependency, needs to be further extracted as to capture more data variations.

The AEM solves this problem by improving the regression model through adding an autoregressive model for the autocorrelation of the errors. As a result, both temporal trend and dependency can be captured, and the regression estimates was corrected for autocorrelation by the AEM method. In our study case, the improvement of model performance is measured by AIC (Akaike’s Information Criterion). The minimum AIC specifies the best model. Figure I-6.1 shows the decreased AIC from OLS to AEM, and their associated p-values for AR terms. The vertical blue lines indicate decreased AIC from OLS to AEM. It is clear to see that, as long as there is a decrease in AIC from OLS to AEM, the associated p-value of at least one of the AR terms will be significant (Figure I-6.1). Finally, it is suggested that AEM improves the parameter estimation for the first 3 miles.

![Figure I-6.1: Increased AIC from OLS to AEM, as well as the associated p-values for AR terms.](image-url)
In addition, AEM can capture the data variations due to both temporal trend and temporal dependency. Figure I-6.2 shows that the estimated values and prediction limits by AEM have variations over time, but constant prediction interval by OLS regression. The feature exposed by AEM has shown the actual case, i.e., smaller values should have lower prediction limits, other than constant prediction limits. Finally, it has minimized the model error and increased the model performance by reducing AIC.
Figure I-6.2: Comparison of modeling shoreline data: a. OLS regression; b. AEM.
7 Conclusion

The shoreline correction process has eliminated the wave and tide effects to some extent on the estimation of shoreline change rate and pattern, which makes the results more accuracy and reliable. The resulting shoreline dataset has a temporal dependency that is significant for the first 2.65 miles, but not from the 2.65 miles point to its south. The periodogram analysis suggests that periodicity existed from Oregon Inlet southward about 2.65 miles. The most common periods of shoreline change is about 1.25 to 5 years. In addition, the results from PCA suggest the variation of shoreline changes is highly concentrated on the first 20 transects (2.65 miles), which was due to the frequent beach nourishment projects conducted in this region. The temporal principal components also emphasized that shoreline changes varied intensively before 1994 and after 2002. This was also explained by the beach nourishment projects conducted in this period. Furthermore, the shoreline change rate for all transects estimated by AEM is a little lower than that estimated by the OLS regression method for the first 2 miles from the Oregon Inlet to its south, but almost the same afterwards. Spatial variability of shoreline change rate also exists from the Oregon Inlet to its south, i.e., the general trend of erosion rate increases from the Oregon Inlet to its south about 2 miles, then decreases for another 2 miles, and increases for the last 2 miles. As a result, special attention needs to be drawn for the 2-mile point from Oregon Inlet southward for the shoreline protection purposes.
Chapter 2 Vulnerability Analysis of Coastal Dunes due to Short-Term Storm Effect through Geomorphology Features

Abstract

The tide/wave conditions and the coastal geomorphology features have been considered as crucial factors in the storm-induced coastal erosion process. In this study, Oregon Inlet region at the east coast of North Carolina has been chosen as the study area, and the Hurricane Isabel, which occurred on September 18, 2003, has been selected as a typical storm event. The airborne LIDAR (LIght Detection And Ranging) data for both bathymetry and topography, has been used as the primary geomorphology data source and applied to spatial feature extraction, wave runup computation, and tide simulation. In order to identify the major factors affecting coastal erosion during a storm, a complete methodology has been developed based on the pre- and post- storm LIDAR data as well the wave/tide computation. (1) Develop and implement the algorithm for automatic identification of the dune crest and dune toe; (2) Compute wave runup alongshore with its spatial variation reflected during the Hurricane Isabel; (3) Simulate and extract the maximum storm tide (astronomical tide and storm surge) with ADCIRC during Hurricane Isabel; (4) Quantify the correlation between dune failure and tide/wave conditions as well as dune features through statistical analysis. The results have proven the ratio of total effective water level (storm tide plus wave runup) over dune crest height and dune height are two key features increasing the probability of dune failure, while the cross-sectional dune profile area is another crucial factor which can prevent dune from eroding. Finally, dune vulnerability with respect to the occurrence probability of dune failure was estimated through Logistic Regression model based on pre-storm dune crest height, dune profile area, dune height and the total effective water level.

Key words: wave runup, storm surge, dune crest, dune toe, LIDAR, Logistic Regression
1 Introduction

Hurricane Isabel, occurred in September, 2003 and caused severe damages to both natural (beach and dune) and man-made (roads and houses) systems on the Outer Banks along the east coast in North Carolina. However, long term observations have shown that coastal dunes can protect upland properties in storm events (Rogers, 2000). As a result, it is crucial to protect the coastal dunes from eroding, and take any necessary actions to recover the dune system after storms. Rogers (2000) has documented successful performance of two beach nourishment projects with hurricane protection dunes in coastal North Carolina. Meanwhile, it is more important to understand the underlying physics of the dune erosion process during storms, for the pre-storm action taken can help better plan the coastal community and avoid further property losses, even save people’s lives (Donnelly et al., 2006). In order to better protect the barrier island from storm induced erosion, lots of research work has been conducted with respect to the storm and wave behavior, as well as the characteristics of the dune system on the barrier island.

Generally, most of the wave energy is dissipated and may not cause current driven sediment transport, when approaching the coast due to the increase of the bottom level. However, the waves can be still sufficiently energetic nearshore during storms, for the storm surge can significantly raise the water level (Wang, et.al. 2005). Sallenger (2000) has investigated that the impact of a storm on a barrier island is dependent not only on the magnitude of storm forced parameters, such as storm surge, wave runup, but is also dependent upon the geometry, particularly the vertical dimension of the barrier island at landfall. Fiore et al. (2009) has emphasized that the storm surge can be more severe if it coincide with a high tide, particularly in the case of the highest astronomical tide. Specifically, the maximum storm surge of 1.49 m coincided with the high tide of 0.56 m resulting in a maximum storm tide of 2.05 m during the Hurricane Isabel at Oregon Inlet in North Carolina. In addition to the storm surge, wave runup is an important factor in the dune erosion process. Stockdon et al. (2006) has summarized the general wave runup function based on the experiments from 10 coastal sites, including Duck, NC. The field experiment supports an empirical formulation for wave
runup, which is a function of the deep-water wave height, deep-water wave length and the foreshore slope. In addition to the storm forced features, dune geomorphology has been further discussed regarding to dune vulnerability for storm-induced erosion (Judge et al., 2003). Sallenger (2000) has proposed Storm Impact Scale and divided the dune into four regimes based on the ratio composed of the effective water level (low and high wave runup) and dune features (crest and toe height). Morton (2002) has concluded that the height and extent of foredune development, relative to the storm tide elevation, are primary controls on the response of a barrier island to extreme storms. However, the combination of all these important findings has not been further developed and applied to a site specific storm event, and the detailed data with high spatial resolution has not previously been available to further advance these findings. Moreover, mathematical modeling intended to predict the dune vulnerability in future storm from an empirical base has not been well developed.

Remote sensing technology, particularly airborne LIDAR (LIght Detection And Ranging) for bathymetric and topographic mapping has gone through extensive development and refinement since the early 1970s. With the high density of LIDAR data, high resolution of topography and bathymetry surfaces become possible and can be applied to coastal geomorphology, wave modeling, and can lead to the advanced knowledge of coastal geomorphic processes (Sallenger et al., 2003, 2007; Mitasova et al., 2009, 2010). Previous work has shown the advantage of LIDAR data with respect to the extraction of geomorphology features (Mitasova et al., 2005; Stockdon et al., 2009). According to the definition, the location of dune crest and toe of an idealized dune may be relatively easy to identify. However, multiple locations of a specific dune crest or dune toe may present due to the complexity of the real data. Consequently, the identification of the features on a wide variety beach system becomes incredible challenging (Stockdon et al, 2009).

As a result, the objective of this study is to develop an automatic extraction methodology of dune features, and apply it to quantifying the spatial variation of dune failure during the Hurricane Isabel. Finally, the dune features along with the wave and storm tide computations were analyzed by a proposed statistical approach to predict the dune vulnerability.
2 Study area and storm description

Oregon Inlet is located at the North Carolina Outer Banks between Bodie Island to the north and Pea Island to the south (Figure II-2.1). Oregon Inlet is a naturally migrating inlet that over a period of 126 years has migrated south at an average rate of 23 m/yr and receded to the west at an average rate of 5 m/yr (Overton et al., 2004). In 1989, a terminal groin was built to stabilize the north end of Pea Island and to protect the Bonner Bridge. Our study area extends from the north end of Pea Island for a distance of approximately 10 km to the south. This region has been chosen as the study area due to the spatial variation of known erosional hot spots and the critical relationship of those hotspots to the NC 12 road (Stone et al., 1991).

Wave and storm tide data is available from the US Army Corps of Engineers Field Research Facility (FRF) located approximately 50 km north of our study area. The maximum significant wave height was 8.12 m with the corresponding peak period of 15.4 sec and wave direction of 103 ND (clockwise from the North). The largest wave measured from the waverider buoy during Hurricane Isabel was 12.1 m, with a nominal depth of 17.0 m. Several waves were observed in the 11-12 m range. The NOAA #11 tide gage recorded the storm tide up to 11:00 am at which time the gage was damaged. The FRF has reconstructed the storm surge hydrograph using data from another gage (#641). Highest storm surge observed during Hurricane Isabel was 1.49 m, with an astronomical tide level of 0.56 m, which resulted in a maximum storm tide of 2.05 m during the Hurricane Isabel. Due to the significance of the storm and the incredible damages caused to the coastal system, essential research work should be conducted to understand the storm forced erosion processes, in order to better protect the coastal system and community in the future.
Figure II-2.1: Study area: a. Plan view; b. 3D view.
3 Data collection and preparation

3.1 Data collection

The data used in this study includes bathymetry, topography (LIDAR data), and wave data. All the spatial data have been projected and referenced to the State Plane 3200 horizontally and NAVD88 vertically in meters.

(1) Bathymetry

The NC topo/bathy grid (Blanton et. al., 2008) was for tide simulation. This high-resolution grid covering the NC coast region and extends inland to the 15 m contour to allow for storm surge flooding.

(2) Topography

The raw topography data is LIDAR data with x, y, z records (longitude, latitude, elevation), collected on September 16, 2003 (pre-storm) and September 21, 2003 (post-storm) by NASA EAARL respectively.

(3) Wave record

The wave data were collected from FRF buoy station, which is located at 36° 10' 6.1" N, 75° 42' 0.8" W, with a nominal depth of 17.0 m. During the Hurricane Isabel, the maximum significant wave height was 8.12 m with the corresponding peak period of 15.4 sec and wave direction of 103 ND.

3.2 Data pre-processing

The LIDAR data (bathymetry and topography) was first converted from ASCII format to the vector .shp format, and then all spatial data was referenced to the same coordinates system, State Plane North Carolina 3200 (horizontal datum) and NAVD 88 (vertical datum) in meters. Preprocessing of the data revealed inconsistencies in the global ground level, and several
locations float over the terrain surface. Thus, both ground control rectification and extreme data removal was required before use to remove known errors.

3.2.1 Data rectification

The data rectification process was conducted based on the GPS data, which was collected along the center line of NC 12 road. By comparing the elevation from the recorded GPS data and elevation extracted from the LIDAR data, error plots of histogram were used to analyze the vertical shift of two LIDAR data sets (Mitasova et al., 2009). By assuming the GPS data represents the real elevation of NC 12, and the elevation of NC 12 center line did not move from 2003 to 2007, we obtained the vertical rectification factors for two data sets (September 16, September 21) based on the most frequent errors. The two rectification factors for the two data sets are +0.167 m and +0.094 m respectively.

3.2.2 Extreme data removal

Neighborhood analysis was performed to exclude the outliers of the rectified LIDAR data. These outliers are recognizable due to their extreme values and are thought to be non-topographic features such as birds or telephone poles. In this study, a 3*3 window was generated to make statistics on the data within the window. If any data within the window have an elevation that is too far away from median elevation, then the data must an outlier, and needs to be excluded before use.
4 Methods

The methodology includes an analysis of the geomorphology to extract key features such as dune crest elevation, dune toe elevation, dune profile area, dune height, dune width and the occurrence of dune failure. In addition, an estimate of the maximum water level and wave runup that occurred during the Hurricane Isabel is determined through a combination of simulation and application of empirically based predictors. Finally, a statistical analysis was performed to document the correlation between the geomorphology response and key antecedent conditions and forcing factors. Figure II-4-1 below is a flowchart showing the whole procedure of dune vulnerability analysis.

4.1 Geomorphology analysis

In the analysis of geomorphology, advanced GIS techniques have been applied to the extraction of the features. Before these features can be extracted, topographic data validation and surface building are the necessary steps to get the correct 3D topography model. In
order to extract the dune crest and dune toe, as well as other features, mathematical algorithms have been developed and applied to the topography data. The extracted features are to be used as the geomorphologic measurements (Figure II-4.2).

![Flow chart of dune toe identification process.](image)

### 4.1.1 Surface building

The rectified LIDAR data was used to build the topographic surface via TIN (Triangulated Irregular Network). The surface values within each triangle were interpolated linearly by using the corresponding triangle based on the data at three vertices. Before this interpolated TIN surface can be used for computation, it is necessary to convert TIN format to raster format. Consequently, data density analysis was performed to find a proper resolution for the converted raster surface. While a coarser resolution will lose some details which could be provided by the raw data, and a finer resolution will add some details that may not exist. Finally, 0.5 m horizontal resolution was chosen based on the data density analysis, and TIN surface data was converted into raster data.
4.1.2 Features extraction

Dune crest and toe are two important features with respect to the geomorphologic patterns of the dune. Feature extraction was conducted based on dune profiles at transects. Hence, the profile view of coastal dune was first plotted at transects. However, before transects can be generated, MHW (Mean High Water) line (elevation contour of 0.36 m) needs to be extracted from the surface data, which serves as the basis of transects generation. Due to the complexity of the real data, a polynomial smoothing algorithm has been applied to improve the continuity of the MHW line (Figure II-4.3). Then, a series of transects were generated, which are perpendicular to the MHW line at a constant interval of 100 m (Figure II-4.4). Finally, dune profiles were created at all transects based on the surface data, which will be used in the feature identification process.

Figure II-4.3: Comparison between the smoothed shoreline and the fuzzy raw shoreline.
Figure II-4.4: Auto-generated transects perpendicular to the shoreline at 100m intervals.

(1) Identification of dune crest

Dune crest is one of the most important features with respect to the geomorphologic patterns of the dune. By definition, the dune crest is the juncture of seaward- and landward-facing slopes (Stockdon et al, 2009). The elevation of the dune crest is crucial to dune’s response during a storm. According to the definition, the dune crest was identified at the location with the local maxima in elevation seaward on each dune profile, which is from the NC 12 to the MHW line. A complete algorithm has been developed as below and applied to all dune profiles. (1) In profile view, the global maxima of elevation should define the dune crest; (2) The absolute values of slopes on either sides of dune crest should be greater than some threshold.
(2) Identification of dune toe

Dune toe is another important feature with respect to the dune geomorphology. Generally, the dune toe was defined as the maximum change in dune slope on the seaward side of the dune profile. Since the dune toe can only appear at the ocean side of the dune crest, the dune profile data was truncated at the location of dune crest to simplify the identification process. As a result, a complete algorithm has been developed to identify the dune toe based on the following criterion. (1) The dune toe should be located where derivative of slope achieves its local maxima; (2) In certain distance from dune toe landward, elevation should be monotone decreasing; (3) Within certain distance from dune toe to the seaward side, the slope should be around zero; (4) Within certain distance from dune toe to the landward side, slope should be less than certain value.

Based on the algorithm, several miss-identified dune toes have been corrected, which is shown below with explanations.

a. More than one local maximum change in slope, improved by proper algorithm (to avoid multi-maxima, Figure II-4.5a);

b. Limit the dune slope at the dune toe to be negative, which indicates a dune heel (to avoid heel, Figure II-4.5b);

c. Search for more steps landward of dune toe to satisfy elevation is monotone decreasing (to reflect big tail, Figure II-4.5c);

d. Search for more steps oceanward of dune toe to satisfy dune slope won’t change much (to reflect flat tail, Figure II-4.5d);

e. Limit the slope landward of dune toe less than some certain value (to avoid flat dune, Figure II-4.5e);

f. Limit the elevation change within certain distance is less than certain value (to avoid trough, Figure II-4.5f).
Figure II-4.5: Dune profile and toe location (left: flawed; right: improved).

Note: The dune slope was multiplied by 100, and the difference of dune slope was multiplied by 10.
Due to the complexity of the real data, it is impossible to automatically identify all the dune toes correctly by using a unified algorithm. As a result, a functional module with a parameter of position adjustment has also been developed in order to make any necessary adjustment to the automatically identified dune toe. By implementing this function, the dune profile along with the location of dune toe can be visualized interactively while user can make adjustment to see if the dune toe is in the right place by alternating the parameters of this function. Finally, with the combination of automatic identification and manual adjustment of dune toe location, all the dune toes have been well identified and located. The location information was then extracted and will be used for the measurement of storm response. Figure II-4.6 below is an example to shown how the identified dune toe was located based on this algorithm in 2D (Figure II-4.6a) and 3D (Figure II-4.6b) view. The spatial examination of both concludes the high accuracy of the dune toe identification makes it liable to be applied to locating dune toe automatically by this methodology.

In addition to dune crest and dune toe, a few geomorphology features were also extracted, such as dune height, dune width and dune profile area. The dune height was defined as vertical distance between the dune crest and dune toe. The dune width was defined as the twice of the horizontal distance between dune crest and dune toe. The dune profile area was defined as the area under dune profile curve and above the plane which is equivalent to the height of the corresponding dune toe.
Figure II-4.6: The identified dune toe overlaid with topography map: a. 2D view; b. 3D view.
4.2 Estimation of wave runup

Runup is the maximum elevation of wave uprush above still-water level. Wave uprush consists of two components: superelevation of the mean water level due to wave action (setup) and fluctuations about that mean (swash). From a statistical point of view, the maximum height it can reach is defined as the $R_{\text{max}}$. If only 2% of waves can run up to or higher than the height, then it is defined as $R_{2\%}$ or $R_2$. Stockdon (2006) has proposed the following form of wave runup equation for general use, which was based on the data from the experiments conducted in 10 coastal sites.

$$ R_2 = 1.1 \left( 0.35 \beta_f (H_0 L_0)^{\frac{1}{2}} + \frac{[H_0 L_0 (0.563 \beta_f^2 + 0.004)]^{\frac{1}{2}}}{2} \right) $$  \hspace{1cm} (4.1)

where, beach steepness $\beta_f$ is the foreshore slope, which was defined by the average slope between the dune toe and MLW level in dune profile view in this study. $H_0$ and $L_0$ are deep-water wave height, and deep-water wave length respectively.

The deep water wave length $L_0$ is relatively easy to obtained, which is only a function of wave period and is formulated by the equation $L_0 = g T^2 / 2 \pi$ .

To compute the deepwater wave height $H_0$, the inversed wave shoaling process along with wave refraction was considered according to the linear wave theory.

$$ H_0 = H_b / (K_R K_S) $$ \hspace{1cm} (4.2)

where

- $H_0 = \text{deepwater wave height (m)}$
- $K_R = \text{refraction coefficient}$
- $K_S = \text{shoaling coefficient}$
- $H_b = \text{significant wave height (m) at the buoy station}$

The refraction coefficient $K_R$ is a function of the deepwater wave angle and the wave angle at buoy station.
where, $\beta_0$ and $\beta_b$ are the wave angle of the deep-water and the buoy station respectively.

The $\beta_b$ can be obtained at the buoy station, and $\beta_0$ can be computed through the Snell’s Law, which is described as the below (Note: The wave angle refers to the angle of the wave ray).

$$\frac{\sin \beta_b}{C_b} = \frac{\sin \beta_0}{C_0} = \text{constant} \quad (4.4)$$

where

$C_0 =$ deepwater wave celerity (m/s)

$C_b =$ wave celerity at buoy station (m/s)

The shoaling coefficient $K_S$ is a function of the group wave velocity at deepwater and the buoy station.

$$K_S = \sqrt{\frac{C_g0}{C_gb}} \quad (4.5)$$

$C_g0$ is the deep-water group wave velocity and only a function of wave period.

$$C_g = \frac{gT}{4\pi} \quad (4.6)$$

$C_g$ is the group wave velocity and defined as

$$C_g = nC \quad (4.7)$$

where, $n$ is the wave number and $C$ is the wave phase speed. They are given by the following equation.

$$n = \frac{1}{2} \left[ 1 + \frac{2kd}{\sinh(2kd)} \right], \quad C = \frac{L}{T} \quad (4.8)$$

The wave length $L$ can be computed through the following dispersion relation.

$$\frac{\omega^2d}{g} = kd \tanh kd, \quad k = \frac{2\pi}{L} \quad (4.9)$$
The wave runup was computed on transects basis, and will be used in the correlation analysis with the coastal responses.

**4.3 Tide simulation**

ADCIRC (ADvanced CIRCulation) is a hydrodynamic circulation numerical model for solving time dependent, free surface circulation and transport problems in two and three dimensions. It utilizes the finite element method in space and therefore can be run on highly flexible, irregularly spaced grids (Westerink et al., 1992). In this study, the tide was simulated with the model ADCIRC starting from the deep ocean. The input data include bathymetry grid (Blanton et al., 2008) and boundary information, model parameters and periodic boundary conditions, nodal attributes, tidal/harmonics components and wind input. The simulation was conducted for a period, which covers the overall Hurricane Isabel event (Vickery, et al., 2008). To avoid underestimating the tide impact on the waves, the maximum storm tide (astronomical tide plus storm surge) over time was used as the water level, which will be further used in the correlation analysis with the coastal response.

**4.4 Statistical analysis**

Logistic Regression analysis is often used to investigate the relationship between these discrete responses and a set of explanatory variables. This approach poses problems for the assumptions of OLS (Ordinary Least Square) that the residuals are normally distributed. In this study, we focused on the occurrence of dune failure with respect to the storm tide, wave runup level, dune profile area, dune height and dune width. The dune failure refers to the situation when the both sides of the dune were significantly eroded and the dune crest was significantly decreased. To quantify this definition for this study, dune failure was defined as the case when dune profile area lost was more than 50% of the original dune profile area. Based on this definition, the occurrence was categorized as dichotomous response variable, 0 and 1. “0” means the dune failure will not occur, and “1” means dune failure will occur under the storm and wave conditions. The equation (4.10) below was used to quantify the relationship between the occurrence of dune failure and explanatory variables.
\[
\ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = b_0 + b_1x_1 + b_2x_2 + \ldots + b_nx_n
\]  

(4.10)

where,

\( \hat{p} \) = estimated probability of the occurrence of the dune failure;

\( x_i \) = explanatory variables, such as storm tide, wave runup, dune profile area, dune height, dune width, or some combination of them, \( i = 1, 2, \ldots, n \);

\( b_0 \) = the intercept needs to be estimated for the model;

\( b_i \) = the coefficients need to be estimated for \( x_i \).

To determine the effective explanatory variables that make contribution to the model, backward elimination method was used to select appropriate variables for the model. The p-value was chosen as the criterion for the significance of the variable, and the AIC (Akaike’s Information Criteria) was computed to determine the best statistical model. A smaller p-value or AIC suggests the significant variable or a better model respectively. For the estimated parameters, a positive regression coefficient means explanatory variable increases the probability of the outcome, while a negative regression coefficient means variable decreases the probability of that outcome; a large regression coefficient means that the risk factor strongly influences the probability of that outcome; while a near-zero regression coefficient means the risk factor has little influence on the probability of that outcome.
5 Result

5.1 Dune geomorphology analysis

Figure II-5.1a and II-5.1b show the pre- and post-storm topographic surfaces of our study area, which goes from the Oregon Inlet (North) to its south about 6 miles. The color from blue to orange corresponds with elevation from low to high, approximately from -3.00 m to 8.67 m. A MHW line in red was overlaid on the topography surface as to distinguish the land region from the ocean. The elevation data on the ocean side of MHW line represents the ocean surface, but not the bathymetry. It is clear to see that features colored in orange are the dune system, spreading from south to north. The variation in elevation of dune ridge is also clearly exposed on the topography surface, especially for the existence of dune break.

Figure II-5.1c shows the topography change map, which is the difference between the pre- and post-storm topography surfaces. A positive value means accretion, and a negative value means erosion during the Hurricane Isabel. The overall view has shown that most of the dune has been experienced erosion, and the accretion mostly appeared at the land side of the dune. This phenomenon may be explained by the cross shore sediment transport process, or the overwash fan developed.
Figure II-5.1: Topographic surfaces: a. September 16, 2003; b. September 21, 2003; c. Change map.
5.2 Storm and wave impact on dune erosion

The maximum storm tide level (green plane) overlaid with the pre-storm topography is shown in 3D view (Figure II-5.2). It has been divided into four segments due to its extreme length from the north to the south, with a segment length of approximately 2.43 km. It is clear that almost the whole beach area was submerged under water during Hurricane Isabel. The most vulnerable region for dune erosion is shown in Figure II-5.2b and II-5.2d. The storm tide level is on the face of the dune but did not overtop the dune. Wave runup process is another important factor, which can destroy the dune, especially during a storm, for the wave energy can be significantly increased due to the elevated water level by storm surge (Wang et. al., 2005). As a result, the impact of wave runup process needs to be considered to determine the dune vulnerability.
The wave impact on dune erosion was quantified as the wave runup level. Figure II-5.3 below shows the MHW level, storm tide level, wave runup, overlaid by the pre- and post-storm geomorphology features, including dune profile, dune crest and dune toe at some typical transects. By adding wave runup to the storm tide level, it is clear to see how the dune
erosion occurred as a result of the storm tide plus wave runup level relative to the height of dune crest. With the investigation at each transect, four types of coastal erosion during the storm have been summarized as below. Figure II-5.3a shows no dune erosion existed, for the level of storm tide plus wave runup is much lower than the pre-storm dune crest. Figure II-5.3b shows partial dune erosion existed, for the level of storm tide plus wave runup is higher but still below the pre-storm dune crest. Figure II-5.3c shows a dune failure, for the level of storm tide plus wave runup is significantly higher than the pre-storm dune crest. Figure II-5.3d also shows a dune failure, but this is due to the dune break existing at this transect. Overall, the beach erosion existed almost everywhere, because the beach was always submerged below the level of storm tide plus wave runup.

---

**Figure II-5.3:** Coastal erosion analysis with respect to dune geomorphology and wave/tide conditions.

- a. No erosion occurred on dune
- b. Partial erosion occurred on dune
- c. Dune failure occurred due to low-lying crest
- d. Dune failure occurred due to the existence of dune break
5.3 Quantitative analysis

5.3.1 Correlative analysis

Figure II-5.4 is showing the elevation of dune crest, water level, as well as the dune failure occurrence. Here we define the level of storm tide plus wave runup as the total effective water level. The blue curve shows the variation of the height of dune crest versus transects ID number, and the green curve represents the variability of effective water level at different transects. The red line shows the occurrence of dune failure (“0” means no occurrence, and “1” means occurrence). By visualizing the plot below, it is suggested a strong correlation between the occurrences of dune failure and the condition that the total effective water level is higher than the elevation of dune crest. Quantitative analysis yields a 67.3% correlation. However, this correlation is not high enough and further quantitative analysis is needed to investigate more significant factors resulting in dune failure.

![Figure II-5.4: Plot of dune crest height, level of storm tide plus wave runup, and dune failure occurrence. Note: the transect ID number indicates it goes from the north to the south with a constant interval of 100 m.](image-url)
Figure II-5.5 is showing the elevation of dune toe, water level, as well as the beach erosion occurrence. The blue curve shows the variation of dune toe height versus transects ID number, and the green curve represents the variability of the level of storm tide plus wave runup at different transects. The red line shows the occurrence of beach erosion (“0” means no occurrence, and “1” means occurrence). Since the dune toe height is always higher than the effective water level, and the beach erosion almost occurred everywhere, a strong correlation between the occurrence of beach erosion and the condition that the effective water level is greater than dune toe height, may exist, but may also depend on others variables, such as beach slope. However, the beach erosion occurrence shows no variability alongshore. Therefore, no further analysis on this can be performed quantitatively.

Figure II-5.5: Plot of dune toe height, level of storm tide plus wave runup, and beach erosion occurrence. 
Note: the transect ID number indicates it goes from the north to the south with a constant interval of 100 m.
5.3.2 Logistic Regression analysis

Logistic Regression analysis based on the AIC model selection method suggested the best model shown in Table II-5.1. It is indicated that explanatory variables, the ratio of total water level (storm tide plus wave runup) over dune crest height, the square root of dune profile area and dune height are significant in determining the occurrence probability of dune failure, for all the associated p-values are less than 0.05 in the Chi-square test. The estimated coefficients for the ratio of total water level over dune crest height, and dune height are positive, which means an increase in the ratio or dune height can increase the possibility of the occurrence of dune failure. Meanwhile, the estimated coefficient for the variable square root of dune profile area is negative, which means an increase in dune profile area will prevent the dune from collapsing. Finally, the estimated model for predicting the probability of occurrence of dune failure can be written as below.

\[
\log \left( \frac{\hat{p}}{1-\hat{p}} \right) = -20.68 + 21.72x_1 - 1.20x_2 + 2.66x_3
\]  

(5.1)

where, \(x_1\) is the ratio of effective water level (storm tide plus wave runup) over dune crest height, and \(x_2\) is the square root of dune profile area, and \(x_3\) is dune height.

Table II-5.1: Logistic Regression analysis of dune failure occurrence data.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>DF</th>
<th>Estimate</th>
<th>Error</th>
<th>Chi-Square</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(b_0)</td>
<td>1</td>
<td>-20.6776</td>
<td>7.3860</td>
<td>7.8377</td>
<td>0.0051</td>
</tr>
<tr>
<td>(b_1)</td>
<td>1</td>
<td>21.7243</td>
<td>6.5353</td>
<td>11.0498</td>
<td>0.0009</td>
</tr>
<tr>
<td>(b_2)</td>
<td>1</td>
<td>-1.1972</td>
<td>0.4279</td>
<td>7.8297</td>
<td>0.0051</td>
</tr>
<tr>
<td>(b_3)</td>
<td>1</td>
<td>2.6590</td>
<td>1.0729</td>
<td>6.1419</td>
<td>0.0132</td>
</tr>
</tbody>
</table>

With the established model, we can estimate the probability of the occurrence of over-top dune erosion. A few examples at different transects are shown below to illustrate how this probability can be estimated (Table II-5.2). With the estimated probability, we can see how
consistent it is between the estimation and the real occurrence. Finally, this validated model can be used for the estimation of dune vulnerability in future storms.

Table II-5.2: Probability estimation of dune failure occurrence.

<table>
<thead>
<tr>
<th>Real Occurrence</th>
<th>Dune Crest Height (m)</th>
<th>Storm Tide Plus Wave Runup (m)</th>
<th>Dune Profile Area (1/2) (m)</th>
<th>Dune Height (m)</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>5.25</td>
<td>4.29</td>
<td>15.27</td>
<td>3.16</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>4.33</td>
<td>4.51</td>
<td>6.13</td>
<td>2.49</td>
<td>0.944</td>
</tr>
<tr>
<td>1</td>
<td>4.06</td>
<td>4.63</td>
<td>6.06</td>
<td>2.20</td>
<td>0.998</td>
</tr>
<tr>
<td>0</td>
<td>5.98</td>
<td>5.10</td>
<td>13.06</td>
<td>3.72</td>
<td>0</td>
</tr>
</tbody>
</table>
6 Discussion

The developed methodology has significantly improved the performance for the features extraction. With the defined algorithm and the developed function module, the geomorphologic feature can be automatically extracted from the surface data. Meanwhile, adequate manual adjustment is also applicable in this function module to improve the accuracy of the extracted features. In addition, the plots of dune profiles overlaid with the wave/tide levels on a transect basis have well exposed the relationship between the wave/tide/dune levels and the occurrence of coastal erosion. This methodology is efficient in finding the effective factors for the analysis on causes and finally leading to model building.

Moreover, in the process of model selection, various situations have been considered with respect to the combination of five explanatory variables, which were dune crest height, water level, dune width, dune height and square root of dune profile area. According to the p-value, dune width is not significant for the model and consequently removed in the preliminary model selection procedure. As suggested by Sallenger (2000), we compared the models using the ratio of total water level over dune crest height with that using the weighted difference between total effective water level and dune crest height. Finally, we found the AIC was significantly decreased by using the ratio as opposed to the weighted difference. Finally, only three variables are included in the model, which are the ratio of total water level over dune crest height, square root of dune profile area and dune height. As a result, the validated model can be used to forecast the dune vulnerability under the given conditions of dune crest, waves and storms.
7 Conclusion

Severe erosion has occurred in our study area with the existence of spatial variation during the Hurricane Isabel in September, 2003. Beach erosion occurred almost everywhere, but the dune failure only occurred under certain conditions. The correlation analysis has shown that, the dune failure will occur with a high probability when the dune crest height is less than the total water level during the storm. Furthermore, Logistical Regression analysis indicated the ratio of water level over dune crest height, square root of dune profile area and dune height are the three major factors which mostly determine the occurrence of dune failure. Finally, the occurrence probability of dune failure has been estimated through the Logistic Regression model based on using field data. Next step includes applying this methodology to addition storm data set, such as Hurricane Dennis 1999.
Chapter 3 Long-term Seasonality of Coastal Waves and Short-term Storm Induced Waves with respect to Beach Erosion through SWAN Simulation

Abstract

Wave propagation and dissipation processes have been considered as important factors with respect to coastal erosion. To well understand these processes, the third-general wave model SWAN was employed to estimate waves in the Oregon Inlet region. The wave gauge station NOAA #44014, at a depth of 47.5 m, was chosen as the source location, from which waves start to propagate. The boundary conditions, which initialize the model SWAN, were defined by the transformed waves from NOAA #44014 station through linear wave theory. The model SWAN was implemented on the domain covering the entire Oregon Inlet region, with a following nested window focused on the coastal region. In order to test the model performance and accuracy, four storm events in 1999, 2003, 2007 and 2010 have been presented as the test scenarios. The observed values were collected from 6 wave gauge stations near the coast. The computed waves were compared with the observations, and the developed Scattered Index (SI) as well as the Model Performance Index (MPI) was used to evaluate the model. Finally, 10-year wave and wind records have been analyzed and categorized into four seasons, which includes significant wave height, peak wave period, mean wave direction, wind speed and wind direction. Typical values of each season for all the variables were chosen based on the histogram analysis. Finally, four scenarios, representing four seasons, have been designed to study the wind-wave variations due to seasonal and spatial effects.

The model performance tests have shown an average of 10% SI and 85% MPI for the four test scenarios, which indicates the computed waves through SWAN are acceptable for the past 10-years. The seasonal simulation scenarios reveal that spring and fall seasons have the same peak wave direction along the coast, which is most likely to result in longshore sediment transport northward. The winter season has relative high wave energy along the coast, but it is almost perpendicular to the coast, which will not be likely to result in
longshore sediment transport. The waves has a component going northward in summer season, but it may not produce longshore sediment transport due to its relative low energy density. In addition, the spatial variation of wave energy alongshore has also been investigated for all seasons. The significant wave height plots at 10 stations have shown wave energy increases with exception of decrease at 2-mile location when it goes southward from Oregon Inlet for all seasons except for winter. On a seasonal basis, fall and winter have the highest wave energy distribution alongshore, while the summer season has the lowest. The wave spectrum analysis has shown that wave energy concentrates on multiple frequencies in fall and winter seasons. In the event of Hurricane Isabel, simulation suggests waves have higher energy at east of Oregon Inlet, and have dominant wave direction from the southeast to northwest. Finally, the cross-correlation between the significant wave height over $d_{50}$ and shoreline change indicates about 64% of the shoreline change variance can be explained by the wave energy and sediment size, which is 0.26 miles southward along 5 m-depth contour.

**Key words: SWAN, Wave Climate, Wave Spectrum, Coastal Erosion, Oregon Inlet**
1 Introduction

The coastal evolution is one of the major concerns of coastal engineers, including coastal sediment transport, shoreline recession, coastal erosion, and so on. Among all the processes, waves are normally the major hydrodynamic forcing in coastal regions (Chen, Wai and Li, 2003). Studies have attempted to relate wave statistics to beach morphology change require some knowledge of the nearshore wave climate (Dail et al., 2000). Therefore, the knowledge concerning wave fields and tides are crucial for the studies of those important aspects of the coastal zone processes (Herman, et al., 2009).

When the wave is approaching the coast, most of the wave energy is dissipated across the surf zone. The energy dissipation process results in an instant increase in current flow, which dominates the sediment transport process. Frihy et al. (2010) and Komar et al. (2008) have documented that the nearshore wave energy is crucial to coastal erosion. Waves are responsible for driving the nearshore current system, and finally result in longshore sediment transport, when the waves approach the coast at an angle. Pleskachevsky et al. (2009) has investigated how the risk of land loss was affected as a matter of nearshore wave energy, which is strongly dependent on the wave climate. The results suggested an increase of intensity in wave climate will more likely to increase the risk of coastal erosion. In addition to the wave energy, wave period is also an important factor which can increase the risk of coastal erosion. Stockdon et al. (2006) has quantified the relation between wave runup and deep-water wave variables, which is a function of wave period. This relation indicates that an increase in wave period will elevate the wave runup, which will consequently increase the risk of the coastal erosion. van Gent et. al. (2008) has performed large-scale physical model tests to quantify the effects of wave period on dune erosion. It was concluded that a longer wave period leads to a larger dune erosion volume and to a larger landward retreat therefore. As a result, the computation of waves near the coasts and beaches becomes important, in order to better understand how the coast regions evolves and to estimate the aftermath risk of coastal erosion, which can be used for better planning of engineer measures and coastal management.
In relative deep water, the wave field is fairly homogeneous on the scale of kilometers, but in the nearshore, where waves are strongly influenced by the variation of bathymetry, water level, wind and current, wave variables may vary significantly on the scale of tens of meters. The offshore wave variables are usually obtained from wave gauge stations. However, comprehensive nearshore wave information cannot be obtained directly with high spatial resolution, due to the lack of gauges (Eshleman et al., 2007). To solve this problem, numerical wave modeling has been well developed and become an essential tool for producing accurate wave estimations and forecasts (Roger et al., 2007; Willis et al., 2010), such as WAM (WAve prediction Model), STWAVE (Steady-State Wave Model) and SWAN (Simulating WAve Nearshore). They play a critical role in the planning, design, implementation, and maintenance of coastal storm protection features.

WAM has been widely used to estimate waves in oceans, in which all relevant processes are included and the wave evolution if formulated on a grid. However, the nearshore wave processes and non-linear corrections to linear wave propagation are not properly resolved in this model, such as the wave diffraction process, wave-wave interactions. In addition, due to the small application region, the computational scheme cannot be efficiently applied to the region with fine resolution (Wornom; Welsh; Bedford, 2001). STWAVE has been developed uniquely for the coastal wave processes. It simulates depth-induced wave refraction and shoaling, wave breaking, wave growth, wave-wave interaction and white capping. The assumptions made in STWAVE are mild bottom slope, negligible bottom friction, steady waves, current and wind. However, for coastal domains where local wave growth is of significance, the steady-state assumption cannot be satisfied. In addition, STWAVE is a half-plane spectrum model, in which only waves propagating toward the coast are represented. Waves reflected from the coast or waves generated by winds blowing offshore are neglected (Breivik, Gusal, Furevik, et. al, 2009). To better estimate the wave field under various conditions, the third-generation wave model SWAN was developed and carried out via the finite element method (Booij, et.al. 1999). SWAN computation can be used to estimate the realistic wave parameters in coastal areas, lakes and estuaries from given wind, bottom and current conditions. The modeled physics associated with SWAN includes wave generation,
propagation, energy dissipation, wave-wave interaction and wave-induced setup. While the underlying wave principles in SWAN have been proved theoretically, the model performance and accuracy have also been validated at the Norwegian Meteorological Institute since 2006 (Ris et al., 1999; Devaliere, Hanson, et al., 2007). Finally, the ability of model SWAN to reproduce the transformation of wave energy in shallow tidal areas was approved in a number of later studies (Kaiser, Niemeyer, 2001; Herman, et al., 2009).

Oregon Inlet is a typical region with special hydraulic pattern. Long-term shoreline evolution process has been monitored here since 1989. The shoreline change rates have been estimated based on the aerial photos and ground survey data (Overton and Fisher, 2003; Overton, 2009). In addition, the variation of temporal and spatial shoreline change rates was also well explained as a result of human activities and natural wave processes (Overton and Fisher, 2004). However, the coastal evolution was not well quantitatively demonstrated as a result of wave-driven sediment transport processes on a numerical model basis. Moreover, the long-term coastal evolution with the seasonal effects, as well as the short-term coastal erosion caused by storms, was not further addressed with respect to the change of wave climate. Therefore, there is such a strong desire to develop a quantitative methodology to investigate the coastal evolution as a matter of wave climate, in order to further benefit the coast management.

In this study, the numerical wave model SWAN was implemented to transform waves from the deep-ocean to the coast region. Seasonal effects as well as the storm events have been considered in SWAN with respect to the wave variations. Finally, the computed waves were used to qualitatively explain the coastal changes in order to understand the variations of coastal erosion as a result of sediment transport process near Oregon Inlet. To clarify the research work, the contributions involved in this study include the following aspects: (1) setup and implement wave model SWAN on both coarse run and nested run; (2) validate the model performance and accuracy under several storm events; (3) apply SWAN to four seasons and a storm event to transform waves from deep ocean to coast region; (4) quantify seasonal waves variation and correlate spatial wave energy with shoreline changes in a storm.
2 Model review

SWAN is the third-generation wave model for obtaining realistic estimates of wave parameters in coastal areas, lakes and estuaries from given wind, bottom and current conditions. It computes the wave propagation from deep water to the surf zone in time and space, shoaling, refraction due to current and depth, frequency shifting due to currents and non-stationary depth, wave generation by wind, nonlinear wave-wave interactions (both quadruplets and triads), white-capping, bottom friction, and depth-induced breaking, wave-induced setup, diffraction, and blocking of waves by current. To achieve this purpose, the integration of the action balance equation has been implemented in SWAN with finite difference schemes in all five dimensions (time, geographic space, and spectral space).

2.1 Wave physics

SWAN contains a number of physical processes, which include wind input, white-capping, bottom friction, depth-induced wave breaking, obstacle transmission, nonlinear wave-wave interactions (quadruplets and triads) and wave-induced setup. These physical processes can be generally categorized into two types, which are wave propagation and dissipation processes.

Wave propagation processes include refraction due to spatial variations in bottom and current, diffraction, shoaling due to spatial variation in bottom and current, blocking and reflections by opposing currents, transmission through, blockage by or reflection against obstacles. In addition, wave generation by wind is also included in the model SWAN.

Wave dissipation processes include white-capping, depth-induced breaking, bottom friction. The details of each dissipation process was described as the below.

(1) White-capping

The process of white-capping in the SWAN is primarily controlled by the steepness of the waves and is represented by the pulse-based model of Hasselmann (1974), reformulated in terms of wave number so as to be applicable in finite water depth.
(2) Bottom friction

The bottom friction models that have been selected for SWAN are the empirical model of JONSWAP (Hasselmann et al., 1973), the drag law model of Collins (1972) and the eddy-viscosity model of Madsen et al. (1988). The bottom friction highly depends on its conditions, like bottom material, bottom roughness length and ripple height.

(3) Depth-induced breaking

The bore-based model of Battjes and Janssen (1978) is used in SWAN, in order to model the energy dissipation in random waves due to depth-induced breaking. The maximum wave height $H_{\text{max}}$ is determined in SWAN with $H_{\text{max}}=rd$, in which $r$ is the breaker parameter and $d$ is the total water depth (including the wave-induced set-up if computed by SWAN)

In addition, the wave-induced setup and nonlinear wave-wave interactions (frequency shifting) can be optionally included in model SWAN.

(1) Wave-induced setup

The computation of the wave-induced setup is based on the vertically integrated momentum balance equation which is a balance between the wave force and the hydrostatic pressure gradient. This approximation can only be applied to open coast (unlimited supply of water from outside the domain) in contrast to closed basin, where this approach should not be used.

(2) Nonlinear wave-wave interactions

Two types of nonlinear wave-wave interactions are available in SWAN, which are quadruplet and triad wave-wave interactions. In deep water, quadruplet wave-wave interactions dominate the evolution of the spectrum. They transfer wave energy from the spectral peak to the lower frequencies and to higher frequencies, where the energy is dissipated by white-capping. In very shallow water, triad wave-wave interaction transfer energy from lower frequencies to higher frequencies, often resulting in higher harmonics.
Wave diffraction

Though wave diffraction is included in the model SWAN, it cannot be properly handled in harbors or in front of reflecting obstacles in SWAN.

2.2 Governing equation

The main goal of the SWAN model is to solve the spectral action balance equation without any a priori restrictions on the spectrum for the evolution of wave growth.

The evolution of the wave spectrum is described by the spectral action balance equation, which, for Cartesian coordinates, is (Hasselmann et al., 1973)

\[
\frac{\partial}{\partial t} N + \frac{\partial}{\partial x} c_s N + \frac{\partial}{\partial y} c_N + \frac{\partial}{\partial \sigma} c_s N + \frac{\partial}{\partial \theta} c_0 N = \frac{S}{\sigma}
\]  

(2.1)

This equation represents the effects of spatial propagation, refraction, shoaling, generation, dissipation and nonlinear wave-wave interactions. The first term on left hand side represents the local rate of change of action density in time, the second and third term represent propagation of action in geographical space. The fourth term represents shifting of the relative frequency due to variations in depths and currents. The fifth term represents depth-induced and current-induced refraction. The expression for these propagation speeds are taken from linear wave theory. The term \( S = (\sigma, \theta) \) at the right-hand side of the action balance equation is the source term in terms of energy density, representing the effects of generation, dissipation, and nonlinear wave-wave interactions.

2.3 Advantages and limitations of SWAN

Several ocean models have been well developed and widely applied to forecasting, but they cannot be applied to the coastal region, for (1) the shallow-water effects of depth-induced wave breaking and triad wave-wave interaction; (2) numerical schemes used are prohibitively expensive when applied to such small-scale, shallow-water regions. As a result, the third-generation wave model SWAN has been developed for coastal regions through extending the formulations of ocean models for deep water and intermediate-depth water by...
adding formulations, which are for depth-induced wave breaking, triad wave-wave interactions, and unconditionally stable numerical schemes. As compared with other wave models, SWAN has several exclusive advantages described below.

- The wave dissipation processes (bottom friction, wave breaking, and white-capping) have been sufficiently represented as nonlinear corrections to linear wave propagation.

- The triad and quadruplet wave-wave interaction have implicitly resolved through LTA (Lumped Triad Approximation) and DIA (Discrete Interaction Approximation) formulations.

- Wave generation by wind has been implicitly represented in SWAN, which is crucial for the applications in coastal regions where storm conditions are often of particular interest.

- The wave diffraction process has been added to the linear wave propagation in SWAN, which is crucial when the area of interest is close to the obstacles on an order of a few wave lengths.

However, a few wave processes still cannot be properly resolved for all the conditions due to the complexity of the reality. These special cases are listed as below.

- Wave-induced set-up can only be computed in open coast, where unlimited supplies of water from outside the domain, in contrast to closed basin, like lakes.

- The wave-induced currents are always ignored, which should be provided by other circulation model as the input for SWAN.

- The diffraction can be only be used where wave height is large within a horizontal scale of a few wave lengths, but diffraction is not explicitly resolved under arbitrary geophysical conditions.

Finally, the application of SWAN on ocean scales is not recommended from an efficiency point of view, though SWAN is derived from ocean models. The WAM model and the WAVEWATCH III model are specially designed for ocean applications.
3 Study area and data preparation

3.1 Study area

Oregon Inlet is located at the North Carolina Outer Banks between the Bodie Island to the North and Pea Island to the south (Figure II-3.1). Oregon Inlet is a naturally migrating inlet that over a period of 126 years has migrated south at an average rate of 23m/yr and receded to the west at an average rate of 5m/yr (Inman, et al., 1989). Today, Oregon Inlet is the only inlet between Cape Henry, Virginia, and Cape Hatteras that provides substantial tidal flow between Pamlico Sound and the Atlantic Ocean (Inman and Dolan, 1989). Our study area is the coast region from the North end of Pea Island to its south about 6 miles. This region has been chosen as the study area, for the existence of the special hydrodynamic feature near Oregon Inlet, as well as the spatial variation of erosion hot spots. The historical record has also shown the significance of both longshore and cross-shore sediment transport.

A few of wave gauges are available in the study area and can be used for the wave monitoring. Those limited numbers of gauges are far from enough for the long coast monitoring. However, it is a good wave data source for the model initialization and verification. Six wave gauge stations were used as the check points for model verification purpose, and one wave gauge station was used as the source point for model initialization. Table III-3.1 has shown the available wave gauge stations along with their properties. The geographic locations of all these wave gauge stations are shown in the Figure III-3.2 below.
Figure III-3.1: Study area in Oregon Inlet.

Table III-3.1: Description of wave buoy gauges near Oregon Inlet.

<table>
<thead>
<tr>
<th>Stations</th>
<th>Names</th>
<th>Longitude</th>
<th>Latitude</th>
<th>Depth</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8m AWAC</td>
<td>-75.743333</td>
<td>36.188333</td>
<td>8.57</td>
<td>Check point</td>
</tr>
<tr>
<td>2</td>
<td>8m Array</td>
<td>-75.742886</td>
<td>36.187239</td>
<td>8.56</td>
<td>Check point</td>
</tr>
<tr>
<td>3</td>
<td>11m AWAC</td>
<td>-75.586750</td>
<td>35.912333</td>
<td>11.37</td>
<td>Check point</td>
</tr>
<tr>
<td>4</td>
<td>Baylor gauge 625</td>
<td>-75.745478</td>
<td>36.183622</td>
<td>6.99</td>
<td>Check point</td>
</tr>
<tr>
<td>5</td>
<td>Wave rider 630</td>
<td>-75.714050</td>
<td>36.199883</td>
<td>17.49</td>
<td>Check point</td>
</tr>
<tr>
<td>6</td>
<td>Wave rider 430</td>
<td>-75.591317</td>
<td>36.257683</td>
<td>25.19</td>
<td>Check point</td>
</tr>
<tr>
<td>7</td>
<td>LLNR 550</td>
<td>-74.836389</td>
<td>36.611111</td>
<td>47.5</td>
<td>Source point</td>
</tr>
</tbody>
</table>
Figure III-3.2: Wave gauge stations in the study area.
3.2 Data collection and preparation

Several types of data with different formats need to be prepared, in order to make the wave model SWAN run. These data include bathymetry grid, wave conditions, wind statistics, tide grid (storm tide).

(1) Bathymetry

The bathymetry data is the integrated grids from various sources with a basic resolution of about 8 m. Two tiles of bathymetry grids were mosaiced to make a single bathymetry dataset in order to have enough coverage for the computational domain. Finally, all the grids have been referenced to the State Plan 3200 horizontally and NAVD 88 vertically in meters.

(2) Wave statistics

The wave information was collected from NOAA buoy station #44014. The wave was characterized as the significant wave height, peak wave period and dominant wave direction. For the simulation purpose, the wave information was finally fitted to the JONSWAP spectral by specifying the peak parameter and directional spreading power.

(3) Wind statistics

The wind was characterized as the direction and speed, and assumed to be a constant over the entire computational domain. The wind information was retrieved from the wind gauge #932, which is located at 36° 11.017' N, 75° 44.70' W with a height of 19.4 m. The direction of wind is measured clockwise from the true north.

(4) Tide statistics

The tide was characterized as the astronomical tide and the storm surge. Due to the lack of data, spatial tide data is not available for our study area. Since the area of our focus is relatively small, we assume that the tide level is spatially constant. Finally, the tide data was obtained from the NOAA station at Duck, NC (#8651370), which is north of the Oregon Inlet.
4 Model setup and implementation

4.1 Definition and conventions

The direction of wind and waves are defined according to Cartesian convention or nautical convention. In Cartesian convention, the direction to where the vector points, is measured counterclockwise from the positive x-axis of this system (in degree). In nautical convention, the direction where the wind or the waves come from, is measured clockwise from geographic North. The default setting for wind and waves is nautical convention, and that for the grid is Cartesian convention. In addition, SWAN expects all quantities that are given by the user to be expressed in S.I. units: m, kg, s and composites of these with accepted compounds, such as Newton (N) and Watt (W).

4.2 Model setup

Three types of model input need to be provided before the simulation can be performed. The first is the command file containing the model implementation script. The second quantifies the bottom, current, friction and wind. The last one describes the wave field at the model boundaries.

In the command file, computational domain was firstly defined with proper coverage and spatial resolution, as well as proper spectral resolution. Grids inputs and boundary conditions were defined and imported with proper parameters. In addition, several wave processes can be optionally included with proper parameters. At last, the computation results can be requested according to the locations and interested variables at the end.

For the quantification of input variables, there are a few types of grids that need to be defined, which includes spectral grids and spatial grids. The spectral grids are 2-D grids, which are determined by the angular resolution and frequency resolution. The spectral information on grids is usually wave energy density, which can be obtained from the nearest wave buoy gauge. The spatial grids include computational spatial grid, input grids and output grids. For the input grids, they are used for bottom, current field, water level, bottom friction and wind.
It is the best to make an input grid bigger than the computational grid. In the region outside the input grid, SWAN assume that the bottom level, the water level and bottom friction are identical to those at the nearest boundary of the input grid. For the current and wind velocity, SWAN takes 0 m/s for points outside the input grid.

To initiate a wave simulation, boundary conditions need to be provided at pre-defined wave boundaries. The boundary conditions are usually represented as the directional wave spectrum. The distribution of wave energy density was characterized by the JONSWAP spectrum, with cosine form of directional spreading coefficient.

### 4.2.1 Wave spectral space

In addition, the basic parameters of wave spectral need to be defined on each spatial grid. These parameters include the extent and resolution of the directional spectrum in both direction-space and frequency-space. While the choice of most of the parameters depends on the available computational resources and academic demand, the grid resolution in frequency-space should satisfies the following condition to avoid DIA approximation error, for the DIA approximation of the quadruplet interactions is based on a frequency resolution of $\Delta f / f = 0.1$. The actual resolution in the computations should therefore not deviate too much from this.

$$\text{[msc]} = \log([f_{\text{high}}]/[f_{\text{low}}]) / \log(1 + \Delta f / f) \quad (4.1)$$

where,

- $[\text{msc}]$: one-less than the number of frequencies in frequency-space
- $[f_{\text{low}}]$: lowest discrete frequency in frequency-space
- $[f_{\text{high}}]$: highest discrete frequency in frequency-space
- $\Delta f / f$: the frequency resolution in frequency-space
In this study, for the frequency-direction space, the wave frequency chosen starts from 0.03 Hz to 1 Hz with 35 discrete frequencies, and the corresponding wave period are from 1 sec to 33 sec. The wave angle covered by the model is the full circle with an increment of 10 degree for the initial coarse run and 7.2 degree for the nested run.

4.2.2 Computational domain

The computation domain covers the area of our interest, and is large enough for the computation of wave propagation to be converged. The computation is implemented on a per cell basis, and covers the wave propagation from the computational boundary to the beach. Millions of computational grids are used to discretize and characterize the computational domain. The computational grid can be structured (uniform, recti-linear, curvi-linear grid) or unstructured (mesh).

In this study, the uniform structure grids were chosen as the basic element of computational domain. The computational grids should be adequately resolved so that enough details of our interest features can be exposed in the output. As a result, the computational grids resolution should be coarser than or equal to the resolution of input grids, such as bathymetry grids and water level grids. Otherwise, higher resolution of computational grids may not improve the computational accuracy due to the lack of details of the input grids. In the meanwhile, coverage area must extend offshore and alongshore far enough to cover all bottom features important for wave transformation to the study area. In this case, the seaward grid boundary should reach beyond shallow, irregular nearshore bathymetry, to where incident wave conditions along the boundary do not change significantly over short distances (Thompson, Smith and Miller, 2004). However, all these physical concerns cannot be satisfied without restrictions, and they must be balanced against the limited computational resources, which are directly related to the total number of grid cells. In order to solve this issue, the nesting computational scheme is well developed in SWAN, which allows coarser computational resolution for larger area and finer resolution for the area of interest, while maintaining a high level of details in our focused region. As a result, in order to reduce computational time
while not lose details of output variables, the model simulation was conducted in two ways, which are initial run and nested run.

(1) Initial run

Generally, the initial run was conducted with coarser resolution for the whole computational domain. The observations or the output from other ocean models are usually taken as the boundary conditions for initial run. All the relevant input grids should have finer or at least equivalent resolution as the computational grids in order to avoid interpolation error.

(2) Nested run

The idea of nesting is to first compute the waves on a coarse grid for a larger region and then on a finer grid for a smaller region. The initial coarse run used the boundary conditions which the user specified based on the wave statistics at buoy gauge or wave hind cast data. The computation on the fine grid uses boundary conditions that are generated by the previous computation on the coarse grid. Nesting can be repeated on ever decreasing scales using the same type of coordinates for the coarse computations and the nested computations.

Finally, for this specific study, the computational domain has coverage of 43 km in the offshore direction and 87 km in the longshore direction with a resolution of 50 m for the initial run (Figure III-4.1). For the following nested run, the computational domain has coverage of 6 km in the offshore direction, and 18 km in the longshore direction with a resolution of 10 m. In the term of number of grid cells, the domain is comprised of 861*1739 grids, which are 1497279 for the initial run. For the nested run, the domain is comprised of 600*1800 grids, which are 1080000 totally.
Figure III-4.1: Computational domain with initial and nested boundaries.
4.2.3 Basic input

Generally, five types of basic input are required by the model, which are bathymetry, water level, current, bottom friction and wind input. Except for the bathymetry, all other basic input can either take a constant value, or have spatial variation over the whole computational domain. For the basic input, the entire input domain will be rasterized into grids if a spatial variation existed in the input data. As a result, one should choose the spatial resolution for the input grids such that the relevant spatial details in these data should be properly resolved. However, the choice of over finer resolution relative to the input data itself will not increase data quality or accuracy, but may adversely reduce the accuracy due to the interpolation error.

(1) Bathymetry grid

The bottom elevation of input region was recorded on the bathymetry grid. The bathymetry grid was rasterized from the elevation data with ASCII format at a resolution of 10 meters based on the density of the raw data. The spatial and vertical coordinate systems have been referenced to the State Plane 3200 and NAVD88 respectively in meters.

(2) Water level grid

The wave level for the storm was directly retrieved from the ADCIRC run. Before it can be used as an input in SWAN, the vertical datum has to be converted from MSL to NAVD88. The software V-datum has been applied to this conversion. In the cases of seasonal waves, in which the ADCIRC simulation cannot be performed, the water level was assumed to be uniform over the computational domain, and the information was retrieved from the nearest tide station, Duck, NC.

(3) Wind input

Due to the small computational domain and the lack of wind data with spatial variation, the wind condition within computation domain was assume to be spatially constant, and was retrieved from the wind gauge #932, in which the measurement was taken 10m above the water surface.
(4) Bottom friction

Generally, the bottom friction with spatial variation cannot be available from large area in real cases. As a result, theories involved with bottom friction have been developed. Three different formulations are available in SWAN for the bottom friction, which are from Hasselmann et al. (JONSWAP), Collins (1972), and Madsen et al. (1988). The JONSWAP formulation is the most popular one among them, and has been widely applied with a constant friction coefficient or with a varying friction coefficient that depends on the frequency-dependent direction spreading.

4.2.4 Boundary conditions

The boundaries of computational grids are either land or water. SWAN does not consider wave reflection, and the land absorbs all incoming wave energy. Usually, waves at these boundaries can be estimated via two ways. One is obtained from the result of another model run or nested run itself, and the other is the observations from the nearest wave buoy gauge.

(1) Boundary definition

There are three types of boundaries, one up-wave boundary (with proper wave information), one closed boundary (waves are absorbed across it) and two lateral boundaries (with no or partial wave information). The input wave boundary should be a little bit inside of the bathymetry coverage to avoid computation errors, for “no data” grid cells sometimes exist along the outer bound of the data coverage. The lateral boundaries should be sufficiently far away from the area of interest to avoid the propagation errors into this area. Such problems do not occur if the lateral boundaries contain proper wave information over their entire length.

(2) Incident wave spectrum

The incoming wave components at the up-wave boundaries in the SWAN model are specified by a parametric one-dimensional spectrum, or discrete one-dimensional spectrum, or discrete two-dimensional spectrum. For a parametric one-dimensional spectrum, three
types of these spectrums are available in SWAN, which are Pierson-Moskowitz spectrum (Pierson and Moskowitz, 1964), JONSWAP spectrum and Gaussian-shaped spectrum.

- **P-M Wave Spectrum**

Pierson and Moskowitz (1964) used a smooth cut-off function, which is zero at low frequencies and unity at high frequencies. The fully developed spectrum, called the Pierson-Moskowitz spectrum, thus obtained is

\[
E_{PM}(f) = \alpha_{PM} g^2 (2\pi)^{-4} f^{-5} \exp \left[ -\frac{5}{4} \left( \frac{f}{f_{PM}} \right)^{-4} \right]
\]  

(4.2)

Where, \(\alpha_{PM}\) is estimated as 0.0081.

This spectrum describes a fully-developed sea with one parameter, the wind speed, and assumes that both the fetch and duration are infinite. This idealization is justified when wind blows over a large area at a constant speed without substantial change in its direction for tens of hours.

- **JONSWAP Wave Spectrum**

The most important wave spectrum is the JOint North Sea Wave Project (JONSWAP; Hasselmann et al., 1973), which is specially developed for the fetch-limited seas. The JONSWAP cannot be applied to swell, because the steepness of swell is low and the shape-stabilising capacity of the quadruplet wave-wave interactions is therefore weaker or practically absent.

\[
E_{JONSWAP}(f) = \alpha_{JW} g^2 (2\pi)^{-4} f^{-5} \exp \left[ -\frac{5}{4} \left( \frac{f}{f_{peak}} \right)^{-4} \right] \exp \left[ \frac{1}{2} \left( \frac{f}{f_{peak}} \right)^{1} \right]
\]  

(4.3)

\(\gamma\) is a peak-enhancement factor and \(\sigma\) is a peak-width parameter \(\sigma = \sigma_a \text{ for } f \leq f_{peak} \text{ and } \sigma = \sigma_b \text{ for } f > f_{peak}\) to account for the slightly different widths on the two sides of the spectral peak. Generally, the average values are \(\gamma=3.3, \sigma_a = 0.07, \sigma_b = 0.09\). \(\alpha_{JW}\) is the scaling
parameter and can be formalized as $0.076 (gF / U_{10}^2)^{0.22}$, where $F$ is the fetch length, and $U_{10}$ is wind speed at the elevation of 10m above the sea surface. However, sometimes it is difficult to compute the $\alpha_{JW}$ for the lack of knowing $F$ and $U_{10}$. So $\alpha_{JW}$ is usually assumed to be a constant and obtained by fitting the JONSWAP spectrum to the real wave spectrum which retrieved from the wave gauge station. The dimensionless spectrums are shown as below (Figure III-4.2). It is clear that the JONSWAP spectrum has a high peak at the peak frequency, as compared with the Pierson-Moskowitz PM spectrum.

![Figure III-4.2: Pierson-Moskowitz PM and JONSWAP spectrum.](image)

For a discrete one-dimensional spectrum, it is characterized as wave energy density versus wave angle for each frequency bin. A discrete two-dimensional spectrum is usually obtained from a previous coarse run by SWAN or other models. For those one-dimensional spectrums, a cosine form with power $m$ needs to be imposed as to describe its directional spreading properties.
(3) Wave Direction Function

The directional spreading of the waves can be defined as the (one-sided) directional width of $D(\theta)$, which characterizes the directional property of the waves. The shape of the distribution $D(\theta)$ is not well known, not even in the idealized situation that we consider here. It is usually speculated that this distribution has a maximum in the wind direction and that it falls off gradually to the off wind direction. Several expressions with this characteristic have been suggested to describe $D(\theta)$. The best-known and probably most widely used is the $\cos^2 \theta$ model (e.g., Pierson et al., 1952).

$$D(\theta) = \begin{cases} \frac{1}{\pi} \cos^2 \theta & \text{for } |\theta| \leq 90^\circ \\ 0 & \text{for } |\theta| > 90^\circ \end{cases}$$  \hspace{1cm} (4.4)

where the direction $\theta$ is taken relative to the mean wave direction. To obtain more flexibility, this model has been generalized to the $\cos^n \theta$ model.

$$D(\theta) = \begin{cases} A_i \cos^n \theta & \text{for } |\theta| \leq 90^\circ \\ 0 & \text{for } |\theta| > 90^\circ \end{cases}$$  \hspace{1cm} (4.5)

where $A_i = \Gamma(\frac{1}{2} m + 1)/[\Gamma(\frac{1}{2} m + \frac{1}{2})\sqrt{\pi}]$ is a normalization coefficient.

(4) Directional Wave Spectrum

$E(f, \theta)$ is called the 2-D or directional energy spectrum because it can be multiplied by $\rho g$ to obtain wave energy. It is a function of both $E(f)$ and $D(\theta)$, i.e.,

$$E(f, \theta) = E(f)D(\theta \mid f)$$  \hspace{1cm} (4.6)

where, $E(f)$ is the energy density spectrum which can be obtained via FFT from the records of wave observations, and $D(\theta \mid f)$ is the directional spectrum which can be either the theoretical wave direction function or obtained from the wave gauge buoy.

The directional distribution $D(\theta \mid f)$ gives the normalized distribution of the wave energy density over directions at one frequency, whereas the two-dimensional spectrum $E(f, \theta)$ gives the non-normalized distribution over both frequency and direction $D(\theta, f)$ may vary with
frequency, but we often use $D(\theta)$, which is also dimensionless. A full 2D directional wave spectrum is shown below (Figure III-4.3) to see its variation over frequencies and directions ($H_s=4.7m$, $T_p=10sec$, $Dir=107\ N\ deg$).

![Figure III-4.3: 2D Directional wave spectrum.](image)

**4.3 Model implementation**

In this study, stationary mode of simulations were conducted in Oregon Inlet region, by assuming all the wave processes, such as wave propagation, growth, and dissipation, do not change much over time. This state assumption is only valid when computational domain is small. Otherwise, significant errors may arise and lead into serious consequence in large domain (Rogers et al., 2007).
4.3.1 Model preparation

To start the initial run, wave conditions along computational boundaries need to be specified or obtained from other sources. However, due to the lack of bathymetry coverage, the source wave gauge, which provides the initial wave conditions, is neither in the computational domain nor along the domain boundaries, so it is necessary to transform the wave from source wave gauge to the domain boundaries (Figure III-4.4).

Figure III-4.4: Wave transformation from source point to the model boundary.

In this study, the initial boundary condition was set at the three sides, i.e., all the sides of the rectangle boundary except for the land side. The incident wave spectrum was collected from the buoy gauge at NOAA #44014, and was then transformed to the computational boundary via linear wave theory. Since the source wave gauge is close to the computational domain boundaries and a little far from the coast, linear wave theory with only wave shoaling and
refraction processes considered may be appropriate to make the wave transformation to the computational boundaries. Finally, the wave conditions along the boundaries are variable and interpolated by the internal model in SWAN. The parameters used to characterize the waves are significant wave height, period, direction, peak enhancement parameter and directional spreading power. In general case, the JONSWAP wave energy spectrum, with the peak enhancement parameter of 3.3, was applied to the capturing wave energy distribution versus frequency. The cosine format of $\cos^2\theta$ was used as the directional spreading coefficient.

### 4.3.2 Modeled physics

In order to make the simulation to be more closed to the reality, several wave physics have been included in the simulation as much as possible, while we consider the computational load. For the wave propagation processes, wave shoaling, refraction processes, and wave generation by wind have been included. For the wave dissipation processes, white-capping, depth-induced breaking, and bottom friction have been considered. Nonlinear wave-wave interactions, such as quadruplet and triad wave-wave interactions, have been also included in this simulation.

### 4.3.3 Output quantities

The output quantities can be controlled by three types of commands. The first one defines the geographic locations of the output, in which the locations can be some points, or some curves, or a pre-defined domain. The second one defines the time range and interval for the output which is requested. The third one requests different types of quantities, which includes wave spectrum, significant wave height, wave periods, average wave direction, directional spreading, energy dissipation, wave setup and so on.

During the computation, SWAN obtains bottom, current, water level, wind and bottom friction information by tri-linear interpolation from the given input grids and time windows. The output is obtained in SWAN by bi-linear interpolation in space from the computational grid. There is no interpolation in time, and output time is shifted to the nearest computational time level.
5 Methods

5.1 Model validation

Before model simulations can be applied to any events for prediction purpose, it is essential to estimate the model accuracy by comparing the measurement at wave gauge stations with the corresponding simulated values in various situations (Goda, 2009; Roger 2007). The potential inaccuracy may be due to the model itself, such as the estimation methods for each wave process, or due to the input data, such as the bathymetry of incorrect date, the desynchronization of wave conditions at different locations.

To establish the scenarios in which we estimate the model accuracy, the selected events should provide a variety of wave and wind conditions, which form a basis for evaluating SWAN application to complex situations. First, we need to estimate the model accuracy at different years in order to compute the inaccuracy due to the bathymetry. Second, we need to choose an event, in which wave should be energetic enough so that most of the wave processes could occur in reality. Third, the wave and wind conditions should be constant within several hours, for the wave conditions at different gauges are not instantly synchronous.

Based on the rules discussed above, four one-hour storm events have been chosen to estimate the performance of the model SWAN. These storm events are on May 2, 1999 (@13:00), April 18, 2003 (@1:00), May 7, 2007 (@7:00), Mar 3, 2010 (@16:00), which are named as Scenario 1, Scenario 2, Scenario 3, and Scenario 4 respectively. In each scenario, the wave simulation starts from the computational domain boundary, along which the wave conditions were initiated by the transformed waves from NOAA wave gauge #44014 through linear wave theory. Six wave gauges are available within the computational domain, which are located at depths from 8m to 26m.
5.1.1 Model initialization

To initiate the model, the wave information at model boundary need to be characterized, which includes the wave spectrum shape, wave conditions (Hs, Tp, Dir), tide statistics and the wind conditions.

(1) Wave spectrum parameterization

For each event, we pick up a one-hour wave statistics from NOAA #44014 during the storm. The spectrum curve, wave energy density vs. frequency, was used to fit the observed wave spectrum as to decide the spectrum parameters. As for the four storm events, Tp is used to control the peak position of the parameterized spectrum, while Hs and gamma (spectrum parameter) are used to control the height of the peak. In addition, the total area under the observations should be equal to that under the parameterized spectrum curve. To satisfy the requirement above, an algorithm has been developed to compute the spectrum parameters, i.e., gammas for the JONSWAP wave spectrum. Finally, the computation shows gammas for the four events are 1.0, 1.3, 1.5, and 2.3 respectively, which will be used to parameterize the spectrum shape (Figure III-5.1).
Figure III-5.1: Observed wave spectrum and parameterized wave spectrum.

a. Scenario 1: May 2, 1999 (@13:00); b. Scenario 2: April 18, 2003 (@1:00)
c. Scenario 3: May 7, 2007 (@7:00); d. Scenario 4: Mar 3, 2010 (@16:00)

(2) Wave boundary conditions

Directional wave spectra from the NOAA #44014 gauge provided the incident spectrum at
the offshore location. The wave spectrum was then transformed to seven locations which
were pre-placed along the computational domain boundary. The transformed wave spectrum
includes the distribution about significant wave height, peak wave period, and average wave
direction. The wave spectrum between each pair of locations was spatially interpolated by the
internal model in SWAN. As a result, we list all the events along with wave conditions below,
which will be used to initiate the simulation.
• Scenario 1: May 2, 1999 (@13:00)

The storm started from 21:16 on April 28, 1999 and lasted for about 108 hours till 9:49 on May 3, 1999. We choose the event at 13:00 on May 2, 1999. At the source point, the wave had a significant wave height of 4.3 m, peak wave period of 12.5 sec, and average direction of 71 N degrees. The associated water level was -0.29 m (NAVD) at 13:00 at Duck, NC. The wind at gauge #932 had a speed of 15.0 m/s, which was coming from 13 degrees clockwise from the North at 13:00 (Table III-5.1).

<table>
<thead>
<tr>
<th>Locations</th>
<th>Depth(m)</th>
<th>Water level(m)</th>
<th>Hs(m)</th>
<th>Tp(s)</th>
<th>Dir(N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23.00</td>
<td>22.71</td>
<td>4.42</td>
<td>12.5</td>
<td>60.30</td>
</tr>
<tr>
<td>2</td>
<td>24.72</td>
<td>24.43</td>
<td>4.39</td>
<td>12.5</td>
<td>60.17</td>
</tr>
<tr>
<td>3</td>
<td>32.39</td>
<td>32.10</td>
<td>4.32</td>
<td>12.5</td>
<td>59.66</td>
</tr>
<tr>
<td>4</td>
<td>32.99</td>
<td>32.70</td>
<td>4.31</td>
<td>12.5</td>
<td>59.63</td>
</tr>
<tr>
<td>5</td>
<td>35.82</td>
<td>35.53</td>
<td>4.30</td>
<td>12.5</td>
<td>59.48</td>
</tr>
<tr>
<td>6</td>
<td>46.00</td>
<td>45.71</td>
<td>4.31</td>
<td>12.5</td>
<td>59.05</td>
</tr>
<tr>
<td>7</td>
<td>37.73</td>
<td>37.44</td>
<td>4.30</td>
<td>12.5</td>
<td>59.39</td>
</tr>
</tbody>
</table>

• Scenario 2: April 18, 2003 (@1:00)

The storm started from 0:00 on April 17, 2003 and lasted for about 79 hours till 1:00 on April 21, 2003. We choose the event at 1:00 on April 18, 2003. At the source point, the wave had a significant wave height of 3.3 m, peak wave period of 10.0 sec, and average direction of 39 N degrees. The associated water level was -0.037 m (NAVD) at 1:00 at Duck, NC. The wind at gauge #932 had a speed of 8.0 m/s, which was coming from 5 degrees clockwise from the North at 1:00 (Table III-5.2).
Table III-5.2: Transformed wave boundary conditions on April 18, 2003.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Transformed wave conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Depth(m)</td>
</tr>
<tr>
<td>1</td>
<td>23.00</td>
</tr>
<tr>
<td>2</td>
<td>24.72</td>
</tr>
<tr>
<td>3</td>
<td>32.39</td>
</tr>
<tr>
<td>4</td>
<td>32.99</td>
</tr>
<tr>
<td>5</td>
<td>35.82</td>
</tr>
<tr>
<td>6</td>
<td>46.00</td>
</tr>
<tr>
<td>7</td>
<td>37.73</td>
</tr>
</tbody>
</table>

- **Scenario 3: May 7, 2007 (@7:00)**

The storm started from 9:00 on May 6, 2007 and last for about 63 hours till 0:00 on May 9, 2007. We choose the event at 7:00 on May 7, 2007. At the source point, the wave had a significant wave height of 5.9 m, peak wave period of 13.79 sec, and average direction of 76 N degrees. The associated water level was -0.013 m (NAVD) at 7:00 at Duck, NC. The wind at gauge #932 had a speed of 17.5 m/s, which was coming from 332 degree clockwise from the North at 7:00 (Table III-5.3).

Table III-5.3: Transformed wave boundary conditions on May 7, 2007.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Transformed wave conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Depth(m)</td>
</tr>
<tr>
<td>1</td>
<td>23.00</td>
</tr>
<tr>
<td>2</td>
<td>24.72</td>
</tr>
<tr>
<td>3</td>
<td>32.39</td>
</tr>
<tr>
<td>4</td>
<td>32.99</td>
</tr>
<tr>
<td>5</td>
<td>35.82</td>
</tr>
<tr>
<td>6</td>
<td>46.00</td>
</tr>
<tr>
<td>7</td>
<td>37.73</td>
</tr>
</tbody>
</table>

- **Scenario 4: Mar 3, 2010 (@16:00)**

The storm started from 19:00 on Mar 2, 2010 and last for about 37 hours till 8:00 on Mar 4, 2010. We choose the event at 16:00 on Mar 3, 2010. At the source point, the wave had a
significant wave height of 5.3 m, peak wave period of 10 sec, and average direction of 32 N degrees. The associated water level was -0.195 m (NAVD) at 16:00 at Duck, NC. The wind at gauge #932 had a speed of 11 m/s, which was coming from 332 degree clockwise from the North at 16:00 (Table III-5.4).

Table III-5.4: Transformed wave boundary conditions on May 3, 2010.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Depth (m)</th>
<th>Water level (m)</th>
<th>Hs (m)</th>
<th>Tp (s)</th>
<th>Dir (N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23.00</td>
<td>22.81</td>
<td>4.96</td>
<td>10</td>
<td>37.7</td>
</tr>
<tr>
<td>2</td>
<td>24.72</td>
<td>24.53</td>
<td>4.97</td>
<td>10</td>
<td>37.0</td>
</tr>
<tr>
<td>3</td>
<td>32.39</td>
<td>32.20</td>
<td>5.07</td>
<td>10</td>
<td>34.6</td>
</tr>
<tr>
<td>4</td>
<td>32.99</td>
<td>32.80</td>
<td>5.08</td>
<td>10</td>
<td>34.4</td>
</tr>
<tr>
<td>5</td>
<td>35.82</td>
<td>35.63</td>
<td>5.12</td>
<td>10</td>
<td>33.8</td>
</tr>
<tr>
<td>6</td>
<td>46.00</td>
<td>45.81</td>
<td>5.29</td>
<td>10</td>
<td>32.2</td>
</tr>
<tr>
<td>7</td>
<td>37.73</td>
<td>37.54</td>
<td>5.15</td>
<td>10</td>
<td>33.4</td>
</tr>
</tbody>
</table>

(3) Tide and wind statistics

The tide and wind information for the simulation period is listed below (Table III-5.5). These values were recorded on a one-hour average, and will be used for the model input.

Table III-5.5: Tide and wind statistics for the computational domain.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Tide level (m, NAVD)</th>
<th>Wind speed (m/s)</th>
<th>Wind direction (d, N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (May 2, 1999)</td>
<td>-0.29</td>
<td>15</td>
<td>13</td>
</tr>
<tr>
<td>2 (April 18, 2003)</td>
<td>-0.04</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>3 (May 7, 2007)</td>
<td>0.01</td>
<td>17.5</td>
<td>31</td>
</tr>
<tr>
<td>4 (Mar 3, 2010)</td>
<td>-0.20</td>
<td>11</td>
<td>332</td>
</tr>
</tbody>
</table>

5.1.2 Model verification

To estimate the accuracy of the model, a scatter index (SI) has been developed (Ris, et al., 1999). It is defined as the rms error normalized by the average of observed value. It is clear that, the lower the SI is, the better performance the model has, i.e., for a perfect model, $SI = \text{rms error}$ is zero.
\[ SI = \frac{rms_{error}}{\bar{X}} \]  
(5.1)

Where, \( rms_{error} = \sqrt{\frac{(X_n - Y_n)^2}{N}} \), \( X_n \) is the observed values, \( Y_n \) is the computed values, \( N \) is the number of observations.

The SI will underestimate the model accuracy in coastal regions, for the index is normalized by the observed values, which are relative small near coast, such as significant wave height. Therefore, the Model Performance Index (MPI) has been developed as to better diagnose the model performance (Ris, et.al. 1999). This index uses the changes between the incident and computed values to normalize the rms errors. The expression for MPI is listed below, with a new term \( rms_{change} \), which is quite the same as \( rms_{error} \) expect for the \( X_i \).

\[ MPI = 1 - \frac{r \sum \Delta X}{r \sum \Delta X + \sum rms_{change}} \]  
(5.2)

where, \( rms_{change} = \sqrt{\frac{(X_n - X_i)^2}{N}} \)

For a perfect mode (\( rms_{error}=0 \)), the value of the MPI would obviously be 1, whereas it would be 0 for model that (erroneously) predicts no changes (\( rms_{error}=rms_{error} \)).

### 5.2 Seasonal waves simulations

The wind-wave variability in the study area is strongly dependent on the wind and the tides, which governs the local wave generation and propagation as well as the wave condition at model boundaries (Herman et al, 2007). Through the period from 2000 to 2009, no statistically significant trend is present in water level on a basis of seasonal categories. So the water level is considered as 0 (NAVD) for all the scenarios below. For other wave or wind variables, statistical analysis for 10-years period was performed to extract the most typical values for each season.

#### 5.2.1 Wave and wind statistics

To estimate the wave impact, the spatial distribution of wave energy needs to be computed through model simulation, which needs wave climate to initiate the model. As a result, wave statistics and wind statistics obtained from NOAA station #44014, have been implemented
for the past ten years from 2000 to 2009. The characterized wave and wind parameters are computed by seasons, i.e., for each season, there are one wave parameter and one wind parameter. The seasons are defined as spring (Mar, April, May), summer (Jun, Jul, Aug), fall (September, October, Nov), and winter (Dec, Jan, Feb). According to the definition and the data collected, histogram for the quantitative variables, and rose plot for the directional variables are shown below.

During the past 10 years from 2000 to 2009, the peak value of significant wave height for the summer is significantly less than that of other three seasons. In addition, the spreading extent of significant wave height histogram in summer is approximately bounded by the upper limit of 2 m, which means less storm events have occurred during the summer, and most storm events occurred during winter. The spring and fall almost have the same statistical pattern of the significant wave height (Figure III-5.2).

Figure III-5.2: Histogram of significant wave height for four seasons from 2000 to 2009.
Figure III-5.3 shows the peak wave period histogram for four seasons. The histograms for spring and fall almost have the same pattern, with a peak value of 9 sec. For the summer, the upper peak wave period is approximately bounded by 10 sec, with its peak around 8 sec. For the winter, the peak wave period is almost uniformly distributed from 5 sec to 10 sec.

Figure III-5.3: Histogram of peak wave period for four seasons from 2000 to 2009.

Figure III-5.4 shows the wave rose for the four seasons, in which the direction is defined as where the wave comes from, measured clockwise from the true North. Again, the spring and fall have quite similar patterns, exception for the component greater than 150 degree. The wave directions with the most occurrences for both spring and fall are coming from the east. For the summer season, most waves come from the southeast. No waves come from the north. For the winter season, the wave direction is more uniformly distributed, with a little bit higher occurrence that it comes from the northeast.
Figure III-5.4: Wave rose for four seasons from 2000 to 2009.

Figure III-5.5 shows the wind speed for four seasons from 2000 to 2009. Spring and fall have almost the same pattern with a peak value of about 5 m/s, and upper bound of about 20 m/s. The spreading of wind speed in summer is a little bit lower, with an upper bound of about 12 m/s. the wind spreading for winter is nearly symmetric about 7 m/s, which indicates wind in winter is generally stronger than that in other seasons.
Figure III-5.5: Histogram of wind speed for four seasons from 2000 to 2009.

Figure III-5.6 shows the wind direction histogram for four seasons from 2000 to 2009. The spring and summer have a quite similar pattern, during which most wind generally comes from the south. Wind direction for fall season has a wider spreading around the north, while wind direction for the winter has a wider spreading around the northwest.
While we are describing the graphs of wave and wind statistics above, we also extract the numerical value with the most occurrences for each variable. Table III-5.6 shows the peak values for each variable in all seasons at NOAA station #44014 from 2000 to 2009, which will be used as wave and wind input conditions for four scenarios.

<table>
<thead>
<tr>
<th>Season</th>
<th>Hs (m)</th>
<th>Tp (sec)</th>
<th>WVD (D, N)</th>
<th>WDS (m/s)</th>
<th>WDD (D, N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spring</td>
<td>0.91</td>
<td>8.36</td>
<td>81</td>
<td>5.20</td>
<td>189</td>
</tr>
<tr>
<td>Summer</td>
<td>0.78</td>
<td>8.45</td>
<td>135</td>
<td>4.67</td>
<td>207</td>
</tr>
<tr>
<td>Fall</td>
<td>0.97</td>
<td>9.17</td>
<td>81</td>
<td>4.90</td>
<td>9</td>
</tr>
<tr>
<td>Winter</td>
<td>1.09</td>
<td>9.00</td>
<td>27</td>
<td>6.70</td>
<td>315</td>
</tr>
</tbody>
</table>

Note: Hs for significant Wave Height, Tp for Peak Wave Period, WVD for Dominant Wave Direction, WDS for Wind Speed, WDD for Wind Direction.
5.2.2 Wave transformation

The wave conditions were transformed from NOAA station #44014 to the model boundary via linear wave transformation, which includes waves of four seasons. The transformed wave conditions for four seasons will be used as the boundary conditions for four scenarios. The Tables III-5.7, III-5.8, III-5.9 and III-5.10 are showing the transformed waves, including significant wave heights, peak wave periods and averaged wave directions, along with the water level in NAVD88.

(1) Scenario: Spring

Table III-5.7: Transformed wave conditions at the model boundary for scenario in spring.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Water level(m)</th>
<th>Hs(m)</th>
<th>Tp(s)</th>
<th>Dir(N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23.00</td>
<td>0.85</td>
<td>8.36</td>
<td>79.48</td>
</tr>
<tr>
<td>2</td>
<td>24.72</td>
<td>0.85</td>
<td>8.36</td>
<td>79.73</td>
</tr>
<tr>
<td>3</td>
<td>32.39</td>
<td>0.88</td>
<td>8.36</td>
<td>80.47</td>
</tr>
<tr>
<td>4</td>
<td>32.99</td>
<td>0.88</td>
<td>8.36</td>
<td>80.51</td>
</tr>
<tr>
<td>5</td>
<td>35.82</td>
<td>0.89</td>
<td>8.36</td>
<td>80.67</td>
</tr>
<tr>
<td>6</td>
<td>46.00</td>
<td>0.91</td>
<td>8.36</td>
<td>80.98</td>
</tr>
<tr>
<td>7</td>
<td>37.73</td>
<td>0.89</td>
<td>8.36</td>
<td>80.75</td>
</tr>
</tbody>
</table>

(2) Scenario: Summer

Table III-5.8: Transformed wave conditions at the model boundary for scenario in summer.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Water level(m)</th>
<th>Hs(m)</th>
<th>Tp(s)</th>
<th>Dir(N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23.00</td>
<td>0.59</td>
<td>8.45</td>
<td>123.09</td>
</tr>
<tr>
<td>2</td>
<td>24.72</td>
<td>0.60</td>
<td>8.45</td>
<td>124.69</td>
</tr>
<tr>
<td>3</td>
<td>32.39</td>
<td>0.68</td>
<td>8.45</td>
<td>130.14</td>
</tr>
<tr>
<td>4</td>
<td>32.99</td>
<td>0.68</td>
<td>8.45</td>
<td>130.46</td>
</tr>
<tr>
<td>5</td>
<td>35.82</td>
<td>0.71</td>
<td>8.45</td>
<td>131.81</td>
</tr>
<tr>
<td>6</td>
<td>46.00</td>
<td>0.77</td>
<td>8.45</td>
<td>134.75</td>
</tr>
<tr>
<td>7</td>
<td>37.73</td>
<td>0.72</td>
<td>8.45</td>
<td>132.57</td>
</tr>
</tbody>
</table>
(3) Scenario: Fall

Table III-5.9: Transformed wave conditions at the model boundary for scenario in fall.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Water level(m)</th>
<th>Hs(m)</th>
<th>Tp(s)</th>
<th>Dir(N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23.00</td>
<td>0.91</td>
<td>9.17</td>
<td>78.94</td>
</tr>
<tr>
<td>2</td>
<td>24.72</td>
<td>0.91</td>
<td>9.17</td>
<td>79.23</td>
</tr>
<tr>
<td>3</td>
<td>32.39</td>
<td>0.93</td>
<td>9.17</td>
<td>80.17</td>
</tr>
<tr>
<td>4</td>
<td>32.99</td>
<td>0.93</td>
<td>9.17</td>
<td>80.22</td>
</tr>
<tr>
<td>5</td>
<td>35.82</td>
<td>0.94</td>
<td>9.17</td>
<td>80.45</td>
</tr>
<tr>
<td>6</td>
<td>46.04</td>
<td>0.95</td>
<td>9.17</td>
<td>80.95</td>
</tr>
<tr>
<td>7</td>
<td>37.73</td>
<td>0.95</td>
<td>9.17</td>
<td>80.57</td>
</tr>
</tbody>
</table>

(4) Scenario: Winter

Table III-5.10: Transformed wave conditions at the model boundary for scenario in winter.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Water level(m)</th>
<th>Hs(m)</th>
<th>Tp(s)</th>
<th>Dir(N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23.00</td>
<td>0.99</td>
<td>9.00</td>
<td>32.16</td>
</tr>
<tr>
<td>2</td>
<td>24.72</td>
<td>1.00</td>
<td>9.00</td>
<td>31.44</td>
</tr>
<tr>
<td>3</td>
<td>32.39</td>
<td>1.04</td>
<td>9.00</td>
<td>29.07</td>
</tr>
<tr>
<td>4</td>
<td>32.99</td>
<td>1.04</td>
<td>9.00</td>
<td>28.94</td>
</tr>
<tr>
<td>5</td>
<td>35.82</td>
<td>1.05</td>
<td>9.00</td>
<td>28.37</td>
</tr>
<tr>
<td>6</td>
<td>46.04</td>
<td>1.09</td>
<td>9.00</td>
<td>27.11</td>
</tr>
<tr>
<td>7</td>
<td>37.73</td>
<td>1.06</td>
<td>9.00</td>
<td>28.05</td>
</tr>
</tbody>
</table>

5.2.3 Wave simulations

To estimate the distribution of wave energy along the coast, wave simulations were performed for each season for the past 10 years. The considered wave processes include wave propagation, wave-wave interaction and energy dissipation. Three output quantities will be focused on as to study the wave the behavior, which includes wave height, period, and direction.

To achieve this purpose, two levels of simulations were conducted, which includes an initial run and a nested run. The initial run was performed over the whole computational domain with a spatial resolution of 50 m, and used to provide boundary conditions for the following nested run. The nested run was focused on the Oregon Inlet area with a finer resolution of 10
In order to better understand how the wave energy spatially distributed, several computational stations have been placed along shore with a constant depth of 5 m. These stations were used to extract wave information, such as wave variables and spectrum.

5.3 Wave simulation during a storm

Waves generated by hurricanes are relatively large and can reach over 10-20 m in sufficiently deep open ocean waters. Even if in the nearshore, waves can be still energetic in that the storm surge can raise the water to a higher level as it is in the deeper ocean (Liu and Xie, 2009). The wave recorded at the FRF site shows that, the largest wave measured from the waverider buoy during the Hurricane Isabel was 12.1 m. The highest storm surge observed during Hurricane Isabel was 1.49 m, with an astronomical tide level of 0.56 m, which resulted in a maximum storm tide of 2.05 m during Hurricane Isabel. The maximum wind gust is 41.3 m/s, with a sustained speed of 35.4 m/s. As a result, in order to investigate the wave impacts during the storm, Hurricane Isabel in 2003 was considered as the representative storm scenario.

5.3.1 Wave transformation

The wave conditions were transformed from the NOAA buoy station #44014 to the model boundary. In order to estimate the strongest waves during the Hurricane Isabel, the maximum significant wave height with the associated peak wave period and average wave direction was used as the input wave condition.

Table III-5.11: Transformed wave conditions at the model boundary for scenario in spring.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Water level(m)</th>
<th>Hs(m)</th>
<th>Tp(s)</th>
<th>Dir(N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>24.19</td>
<td>8.12</td>
<td>15.4</td>
<td>107.96</td>
</tr>
<tr>
<td>2</td>
<td>25.66</td>
<td>8.15</td>
<td>15.4</td>
<td>109.32</td>
</tr>
<tr>
<td>3</td>
<td>33.27</td>
<td>8.42</td>
<td>15.4</td>
<td>115.99</td>
</tr>
<tr>
<td>4</td>
<td>33.82</td>
<td>8.45</td>
<td>15.4</td>
<td>116.45</td>
</tr>
<tr>
<td>5</td>
<td>36.57</td>
<td>8.60</td>
<td>15.4</td>
<td>118.73</td>
</tr>
<tr>
<td>6</td>
<td>46.65</td>
<td>9.47</td>
<td>15.4</td>
<td>126.85</td>
</tr>
<tr>
<td>7</td>
<td>38.63</td>
<td>8.74</td>
<td>15.4</td>
<td>120.41</td>
</tr>
</tbody>
</table>
5.3.2 Storm simulation

In order to improve the model performance, the result from ADCIRC run was used to provide the spatially distributed water level, instead of the spatially homogenous water level. To estimate wave energy distribution, the simulation was conducted at two levels, initial run with coarse resolution (50m), and the nested run with finer resolution (10m). The initial run was performed for the whole computational domain and provides the spectral boundary for the following nested run. The nested run was only focused on the Oregon Inlet area. Several computational stations have been placed along the coast, in order to better show the spatial distribution of the storm waves.

5.3.3 Wave-induced coastal evolution

Wave is one of the most important factors that drives sediment transport and cause coastal erosion during storms. In addition, the sediment size is proportional to the fall velocity and consequently determines the sediment transport. This relation has been documented by Baldock et al. (2010). To investigate the impacts of both wave energy and sediment size on coastal change, the pre- and post- storm MHW line (0.36 m contour) was derived from the corresponding topography. The shoreline changes are measured by the distance along the pre-defined transects, and the $d_{50}$ was computed at each corresponding transect location. Finally, the cross correlation between the significant wave heights on 5 m contour over $d_{50}$ and the shoreline changes was computed, in order to see how much variation of shoreline change can be explained by the wave energy as well sediment size.
6 Results

6.1 Model validation

The wave conditions at those wave gauges were extracted from the simulation. The corresponding wave statistics from wave gauges were also collected. A comparison plot below has clearly shown the differences between the simulated wave height and measured wave height.

(1) Scenario 1: May 2, 1999 (@13:00)

Figure III-6.1 shows the comparison between the observed and computed $H_s$ over gauge stations. The wave statistics at gauge 1, 3, and 5 were not available at 13:00 on May 2, 1999. The estimated SI and MPI are 0.08 and 0.75 respectively, which means 75% of wave changes due to transformation can be predicted by the model.

![Figure III-6.1: Comparison between observed and simulated significant wave height.](image)

Figure III-6.1: Comparison between observed and simulated significant wave height.
(2) Scenario 2: April 18, 2003 (@1:00)

Figure III-6.2 shows the comparison between the observed and computed $H_s$ over gauge stations. The wave statistics at gauge 1, 3, and 5 were not available at 1:00 on April 18, 2003. The estimated SI and MPI are 0.15 and 0.76 respectively, which means 76% of wave changes due to transformation can be predicted by the model.

![Figure III-6.2: Comparison between observed and simulated significant wave height.](image)

(3) Scenario 3: May 7, 2007 (@7:00)

Figure III-6.3 shows the comparison between the observed and computed $H_s$ over gauge stations. The wave statistics at gauge 1, 3, and 5 were not available at 7:00 on May 7, 2007. The estimated SI and MPI are 0.12 and 0.78 respectively, which means 78% of wave changes due to transformation can be predicted by the model.
(4) Scenario 4: Mar 3, 2010 (@16:00)

Figure III-6.4 shows the comparison between the observed and computed $H_s$ over gauge stations. The wave statistics at gauge 1 through 6 were all available at 16:00 on Mar 3, 2010. The model performed fairly well at all stations except for #6. Since station #6 is a little bit from the coast, we can exclude it when validating the model performance. Finally, the estimated SI and MPI for 5 stations are 0.05 and 0.92 respectively, which means 92% of wave changes due to transformation can be predicted by the model.
Figure III-6.4: Comparison between observed and simulated significant wave height.

Overall, the model has an averaged 10% scattered error for the scenarios discussed above. The performance test indicated that approximately 80% changes due to wave transformation can be predicted by the model. Therefore, these values will be used to estimate the model performance in the following scenario simulations.

6.2 Seasonal waves variability

6.2.1 Wave height

The computed maximum wave heights in our study area are 1.03 m for spring, 0.84 m for summer, 1.16 m for fall, and 1.25 m for winter. Figure III-6.5 below has shown a higher wave energy distribution near both ends of Oregon Inlet. It is also clear to see the spatial variation of wave energy along the coast for the four seasons, i.e., the general trend of wave energy increases as it goes from the Oregon Inlet to its south.
Figure III-6.5: Significant wave height for seasonal scenarios during the period from 2000 to 2009.
 a. Spring; b. Summer; c. Fall; 4. Winter.
Figure III-6.6 shows the spatial variation of significant wave height over the 10 pre-defined stations. It is very clear that the significant wave height has a sharp decrease at station #3 almost for all seasons when it goes from station #1, and then it goes up smoothly until station #10. However, the variation pattern is a little bit different for the significant wave height in winter. It is about the same height for the first 5 stations, and a little bit lower for the last 5 stations.

![Figure III-6.6: Significant wave height at 10 pre-defined stations for four seasons.](image)

6.2.2 Wave period

The results show that the computed peak wave period is spatially homogeneous for each season, but has small variations among seasons. While the spring and summer seasons have a shorter peak wave period of 8.37 sec, the fall and winter seasons have a longer peak wave period of 9.31 sec. Based on the linear wave theory, the wave length in deep water is formatted as \( L_0 = \frac{gT^2}{2\pi} \), which means longer wave period results in longer wave length. Also, as a result from wave runup analysis, the wave runup is positive related with the deep-water wave length \( L_0 \), which is one of the most important factors on the coastal erosion
(Stockdon, 2006). Therefore, the wave period analysis indicates that fall and winter seasons have longer peak wave periods and higher wave runup than that in spring and summer seasons, which will be more likely to result in more severe coastal erosion.

6.2.3 Wave direction

Figure III-6.7 shows the averaged wave direction for each season in the study area. The seasonality of the offshore wave direction is significant. The spring season has a dominant waves coming from the east (67.5°-90°), while the summer season has a dominant waves coming from the southeast (112.5°-135°). The averaged wave directions in fall and winter seasons are dominated by northeast (22.5°-67.5°) direction offshore.
Figure III-6.7: Average wave direction for seasonal scenarios during the period from 2000 to 2009.
   a. Spring; b. Summer; c. Fall; 4. Winter.
6.2.4 Wave spectrum

(1) Wave energy-frequency space

Figure III-6.8 shows how the wave energy density is distributed over frequencies from the Oregon Inlet to its south for four seasons. It is clear that the wave energy density at dominant frequency is almost always the highest in fall season, which is consistent with the conclusion based on the significant wave height distribution above. While dominant frequency for all the seasons is around 0.12 Hz, the spring and summer seasons have higher dominant frequency. In addition, the fall and winter seasons have another higher energy band on the spectrum tail. The higher energy frequency for fall season is around 0.23 Hz, and that for winter season is around 0.30 Hz.
Figure III-6.8: Wave spectrum at 10 pre-defined stations for four seasons.
(2) Wave energy-direction space

Figure III-6.9 shows the wave energy distribution over directions at 10 pre-defined stations near the coast. It is clear that the spring and fall seasons have almost the same energy distribution, which are focused at the direction around 100-110 degrees relative to the coast. This may result in longshore sediment transport from the south to the north. For the wave energy distribution in winter, it almost concentrates on about 90 degrees relative to the coast, which is not likely to result in any longshore sediment transport. The wave energy in summer season is focused on the direction of 120 degrees relative to the shoreline, though it is not as strong as that in other seasons. This feature is also probably to result in longshore sediment transport from the south to the north.
Figure III-6.9: Wave energy distribution over wave directions along coast.

*Note:* angles are relative to the coast line.
6.3 Storm induced waves

Figure III-6.10 has revealed the spatial variation of the significant wave height during the Hurricane Isabel in 2003. It is clear to see that waves have higher energy at the southeast of the computational domain, and strong variation of wave height along the coast. In addition, waves come from the southeast of the Oregon Inlet, and may result in sediment transport from the south to the north.

![Figure III-6.10: Computed waves during the Hurricane Isabel in 2003: a. 50m initial run; b. 10m nested run.](image)

6.3.1 Wave height

Figure III-6.11 below shows the spatial distribution of significant wave height during the Hurricane Isabel. The significant wave heights are sampled at 10 computational stations. A trend of increasing wave heights exists when it goes from the Oregon Inlet to its south, with
the exception at station #2 and station #5. The result indicates that the region near station #2 and #5 is less likely to be eroded during the Hurricane Isabel. The region at station #4, about 3 miles from the Oregon Inlet, is more likely to be eroded during the hurricanes, if considering only the wave energy.

![Graph showing significant wave height along coast during Hurricane Isabel.](image)

Figure III-6.11: Significant wave height along coast during the Hurricane Isabel.

### 6.3.2 Wave direction

Figure III-6.12 below shows how the wave energy distributes over directions during the Hurricane Isabel. There is a trend that all the waves travel from the south to the north based on the wave direction at all computational stations. This indicates that the longshore sediment transport during the Hurricane Isabel is from the south to the north. As a result, more erosion may have occurred in the south part of the study area due to the longshore sediment transport.
Figure III-6.12: Wave energy distribution over directions along coast during Hurricane Isabel.

**Note:** all the angles are relative to the shoreline.
6.3.3 Waves impacts on coast

Figure III-6.13 shows the shoreline change and significant wave height measured from the Terminal Groin of the Oregon Inlet. The significant wave height was divided by the estimated $d_{50}$, say $H_s/d_{50}$, and the cross-correlation between $H_s/d_{50}$ and the shoreline change yielded a coefficient of 0.64, with the associated lag of 0.26 miles. This indicates that the shoreline change was mostly dependent on $H_s/d_{50}$, which is 0.26 miles south alongshore. A positive value suggests higher significant wave height or smaller sediment size will result in higher shoreline change landward (erosion). Though the cross-correlation coefficient is not high, the shoreline change during Hurricane Isabel is partially explained by the wave energy and sediment size.

Figure III-6.13: Shoreline change and significant wave height vs. distance during Hurricane Isabel.
7 Discussion

The wave model SWAN has successfully transformed the waves from the deep ocean to the nearshore, which helps the further analysis of wave impacts on the coastal erosion. During the transformation process, most of the wave processes are included in the simulation, such as nonlinear processes, in addition to the linear wave process. However, there are a few issues that need to be further discussed for the whole computation process.

(1) Data accuracy

First of all, the data accuracy is an important issue. Figure III-7.1 below shows the computation errors of significant wave height (blue dots) where “no data” cells exist in the bathymetry data (Figure III-7.2). The reason that the “no data” cells appear after the mosaicing process is due to the conversion from the geographic reference system to the State Plane projection system, which made the cells along the contact between two tiles tilt and cannot be exactly connected to each other without gaps. As a result, these flaws in bathymetry data lead into none convergence in model computation.

![Figure III-7.1: Computational error when “no data” cells exist in the bathymetry.](image)

![Figure III-7.2: Seams in the mosaiced bathymetry data and a 3*3 window over “no data” pixels.](image)
In order to fix this problem, a mathematical algorithm has been developed, i.e., a 3*3 window was centered on each “no data” grid cell after two pieces of data were mosaicked. The mean value around each “no data” grid cell was used to fill in the associated “no data” grid cell. Finally, 5480 “no data” cells were found and well fixed in the mosaiced bathymetry by this method. Second, the unique bathymetry data applied to all scenarios is not the one exactly matches the data on which the simulation was conducted for. This assumes the bathymetry in the computational domain does not change significantly over time. However, this assumption may be violated nearshore, for the strong wave-bottom interaction or the sand dredging projects may have changed bottom level. Thus, the availability of time series bathymetry data can improve the accuracy of input data for the model.

(2) Model performance

Waves were transformed from the deep ocean to the coast region through the combination of linear wave transformation and model SWAN simulation. For the linear wave theory with only shoaling and refraction processes may not cover all the wave processes which could exist in the reality, the transformation from the source point to the computational domain boundary may bring in some errors. Though the results of simulation are reliable and acceptable, some work is still needed to improve the model performance. Jeff Hanson (2010) has investigated the coastal response by numerical modeling. In his work, three models are employed, which are ADCIRC, WAVEWATCH III and SWAN. The model ADCIRC was used to compute the water level and current, which was taken as one of the inputs for SWAN and WAVEWATCH III. The WAVEWATCH III was used to provide the spectral boundary conditions for the model SWAN. Finally, the numerical results from the model SWAN provided the necessary outputs for the coastal wave processes.

Moreover, all the simulations in this study were operated under the stationary process due to the relatively small computational domain. However, in some certain situations, the assumption of stationary wave propagation may be violated, especially for the storm events. In addition, due to the lack of spatial data, homogenous wind was used in all the scenarios, by assuming it is spatially constants in the computational domain. Considering the
computational domain is small, this assumption may not bring in too much error to the final results.

(3) Sediment transport

The wave model SWAN has been applied to the estimation for both seasonal waves and waves during the Hurricane Isabel. The purpose is to shown the spatial distribution of wave energy, and to further explain the spatial variation of shoreline changes as well as the consequent sediment transport direction. For the seasonal waves, the distribution of averaged wave computed by SWAN highly depends the input wave climate at the model boundary. Thus, the consequent results by SWAN can only show a typical case during the period from 2000 to 2009. In this scenario, the computed waves have a typical trend travelling from the south to the north, and may cause sediment transport from the south to the north consequently. However, there may be different sediment transport directions during this period. Miller et al. (1996) concluded there was southward sediment transport from 1994 to 1996. He also found northward sediment transport dominated during 1991 through 1993.

In addition to the sediment transport direction, the correlation between $H_s/d_{50}$ and shoreline changes was quantified during the Hurricane Isabel. The cross-correlation is not high, but has indicated the wave energy and sediment size are dominant factors and they can partially explain the spatial variation of coastal erosion. The computed wave energy was also intended to correlate with the occurrence of dune failure in Chapter 2. A brief comparison shows wave energy is higher southward, and also the occurrence of dune failure is higher. Therefore, dune failure is correlated with the wave energy to some extend from this point of view. In future work, more variables will be considered, such foreshore slope, wave direction, in order to the quantitatively model the sediment transport process during storms.
8 Conclusion

The seasonality of the wave climate is remarkable in the Oregon Inlet area, which include the significant wave height, peak wave period and averaged wave direction. The numerical simulation suggests that the wave energy alongshore in fall and winter is higher, while that in summer is lower, which indicates that the coast in fall and winter seasons may have higher potential erosion than that in the summer season. In addition, spatial variations in wave field are also significant from the Oregon Inlet to its south. There is a general trend of increasing wave height from the Oregon Inlet to its south for all seasons, with exceptions of remarkable decreases in wave height about 2 miles south of Oregon Inlet due to the special hydraulic pattern. Moreover, the estimated peak wave periods suggest that it is shorter for the spring and summer seasons and longer for the fall and winter seasons. Thus, longer waves exist in fall and winter seasons, and may cause more intensive coastal erosion due to higher wave runup. In the wave energy-direction space, waves are more concentrated on the direction from the southeast, except for the waves in winter which is almost perpendicular to the shoreline. As a result, sediment transport is more likely to occur northwards in Oregon Inlet region, with exceptions of southwards during 2000 through 2009.

In the event of Hurricane Isabel, waves have higher energy at the east of Oregon Inlet, and have dominant wave direction from the southeast to northwest. In addition, the significant wave height increases when it goes from the Oregon Inlet to its south, with the exception at about 1 mile and 4 mile from the Oregon Inlet. In the direction-energy space, all the waves come from the southeast to the northwest, and may cause sediment transport from south to north alongshore. Finally, the cross-correlation between the significant wave height over $d_{50}$ and shoreline change indicates about 64% of the shoreline change variance can be explained by the wave energy and sediment size, which is 0.26 miles southward along 5 m-depth contour.
References


[68] Willis, M.C., Devaliere, E., Hanson, J. et al., 2010. Implementing the SWAN wave model at three east coast National Weather Service offices.
