Summer 2017

Investigating Physical Processes Associated With Chesapeake Bay and Changjiang Estuary

Arash Niroomandi
Old Dominion University

Follow this and additional works at: https://digitalcommons.odu.edu/cee_etds

Part of the Civil Engineering Commons, Climate Commons, and the Oceanography Commons

Recommended Citation

This Dissertation is brought to you for free and open access by the Civil & Environmental Engineering at ODU Digital Commons. It has been accepted for inclusion in Civil & Environmental Engineering Theses & Dissertations by an authorized administrator of ODU Digital Commons. For more information, please contact digitalcommons@odu.edu.
INVESTIGATING PHYSICAL PROCESSES ASSOCIATED WITH CHESAPEAKE BAY AND CHANGJIANG ESTUARY

by

Arash Niroomandi
B.Sc., May 2007, Azad University
M.Sc., Dec. 2009, Sharif University of Technology

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirement for the Degree of

DOCTOR OF PHILOSOPHY
CIVIL & ENVIRONMENTAL ENGINEERING

OLD DOMINION UNIVERSITY
August 2017

Approved by:

__________________________
Gangfeng Ma (Director)

__________________________
Tal Ezer

__________________________
Navid Tahvildari
ABSTRACT

INVESTIGATING PHYSICAL PROCESSES ASSOCIATED WITH CHESAPEAKE BAY AND CHANGJIANG ESTUARY

Arash Niroomandi
Old Dominion University, 2017
Director: Dr. Gangfeng Ma

Coastal and estuaries are landforms that not only have great impacts on large marine ecosystem, but also play a significant role in moderating or aggravating natural hazards and erosion risks that are expected to increase with climate change. This dissertation explores some of the concerns associated with coasts and coastal systems. In the second chapter, a thirty seven year wave hindcast (1979-2015) in Chesapeake Bay using NCEP’s Climate Forecast System Reanalysis (CFSR) wind is presented. The long-term significant wave heights are generated by the third-generation nearshore wave model SWAN, which is validated using the wave height measurements at buoy stations inside the bay. Validation results show a good agreement between simulations and measurements. Statistical analyses on the simulated wave heights are carried out. Firstly, an Empirical Orthogonal Function (EOF) analysis is performed to study the temporal and spatial variability of significant wave heights in the bay. Secondly, the long-term changing trends of extreme wave heights are examined using regression analysis and empirical cumulative distribution function approach, which reveal a steady increase of extreme wave heights in most parts of the Chesapeake Bay in the past several decades. Finally, extreme value analyses based on generalized extreme value and generalized Pareto distribution functions are applied to evaluate design wave heights with different return periods. The effects of key parameters including threshold value, time span and data length on the design wave heights are extensively studied. Through the comparisons of different distribution functions evaluated by Bayesian Information Criterion and Akaike Information Criterion, it is found that Gamma distribution function and generalized extreme value analysis provide the best fit for annual and monthly data, while generalized Pareto distribution function gives the best fit when peak-over-threshold analysis is conducted. In the third chapter, sediment deposition in the north passage of the Changjiang Estuary, where the Deep-water Navigation Channel (DNC) is located, has been studied. To understand the suspended sediment dynamics and the effects of sediment-induced stratification on sediment flux in the navigational channel,
field data on tidal flow and suspended sediment concentration (SSC) are collected and analyzed in this study. It is shown that net sediment transport is dominated by ebb currents in the study area. The net sediment flux is generally toward the ocean and the maximum value is found to be in the middle reach of the passage. In the lower reach of the passage, the net sediment flux is landward in the lower layer and seaward in the upper layer of the water column due to the two-layer feature of the estuarine circulation. Advective flux plays a significant role in transport of sediment in upper and middle reach of the passage by carrying 70~100% of the suspended sediment. However, this amount is reduced to 30~60% in lower reach of the passage where tidal effects become more important. The suspended sediment induced stratification in the north passage is examined by calculating eddy viscosity. It is found that suspended sediment can reduce eddy viscosity by 10~30%. The highest depth-averaged SSC is located in the middle reach of the north passage, where the averaged SSC is 4~15 times higher than that in the upper reach. In this region, bed shear stress is larger at ebb while SSC is higher at flood. It is inferred that suspended sediments in the DNC during flood are partially transported from a neighboring shoal, which plays an important role in sediment dynamics in the north passage.
ACKNOWLEDGEMENTS

I would like to thank my advisor Dr. Gangfeng Ma for supporting me during my PhD studies, for invaluable help and practical suggestions; I would also like to thank my committee members Prof. Tal Ezer and Dr. Navid Tahvildari for their helpful suggestions on the dissertation and enriching the quality of this research. I would like to express my sincere gratitude to Dr. Asghar Bohluly and Dr. Morteza Aboutalebi for helping in my academic and professional career. Away from the lab I have been fortunate to meet many interesting people. Among them I would like to express my gratitude to Stan and Julia, Doug and Diane for their support and help and their true friendship. And finally, I must thank my family, whom from afar have provided so much love and support. To Mum, Dad, Siamak and Arsalan; thanks for the calls, emails and the delicious cookies and nuts.
# TABLE OF CONTENTS

## LIST OF TABLES

<table>
<thead>
<tr>
<th>List of Tables</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>vii</td>
</tr>
</tbody>
</table>

## LIST OF FIGURES

<table>
<thead>
<tr>
<th>List of Figures</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>x</td>
</tr>
</tbody>
</table>

## CHAPTERS

1. Introduction .................................................. 1

2. Statistical Analysis of Waves in Chesapeake Bay ................. 8
   2.1 Introduction ................................................. 8
   2.2 Study area ................................................... 10
   2.3 Wind data and model validation ............................... 12
   2.4 Statistical analyses of SWHs ................................ 14
      2.4.1 EOF analysis ............................................. 14
      2.4.2 Regression analysis ..................................... 19
      2.4.3 Extreme value assessment ................................ 23
   2.5 Discussions .................................................. 35
      2.5.1 Threshold and time span .................................. 35
      2.5.2 Distribution functions ................................... 38
      2.5.3 Length of data used in the analysis ...................... 43
   2.6 Summary ...................................................... 45

3. Sediment processes in the Changjiang Estuary .................... 47
   3.1 Introduction .................................................. 47
   3.2 Study area and field surveys ................................ 51
   3.3 Results ....................................................... 53
      3.3.1 Flood-ebb asymmetry and fortnightly variability ........ 53
      3.3.2 Sediment transport fluxes ................................ 57
   3.4 Discussions .................................................. 62
      3.4.1 Sediment-induced stratification .......................... 62
      3.4.2 Bed shear stress and sediment sources ................... 67
   3.5 Summary ...................................................... 74

4. Conclusions and Future Works .................................... 75

## APPENDICES

VITA ................................................................. 93
## LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Name and occurrence time of hurricanes and tropical storms inside Chesapeake Bay for the past decade</td>
<td>18</td>
</tr>
<tr>
<td>2.2</td>
<td>Return levels using annual maxima and different parameter estimation methods</td>
<td>31</td>
</tr>
<tr>
<td>2.3</td>
<td>Return levels using monthly maxima and different parameter estimation methods</td>
<td>31</td>
</tr>
<tr>
<td>2.4</td>
<td>Return levels using POT analysis (threshold= 1m, $\Delta t = 3$ days) and different parameter estimation methods</td>
<td>35</td>
</tr>
<tr>
<td>2.5</td>
<td>Return levels for time span $\Delta t = 3$ days and various thresholds</td>
<td>36</td>
</tr>
<tr>
<td>2.6</td>
<td>Return levels for time span $\Delta t = 4$ days and various thresholds</td>
<td>36</td>
</tr>
<tr>
<td>2.7</td>
<td>Return levels for time span $\Delta t = 5$ days and various thresholds</td>
<td>37</td>
</tr>
<tr>
<td>2.8</td>
<td>Return levels for time span $\Delta t = 6$ days and various thresholds</td>
<td>37</td>
</tr>
<tr>
<td>2.9</td>
<td>Summary of AIC and BIC values calculated from different models using annual maxima data</td>
<td>39</td>
</tr>
<tr>
<td>2.10</td>
<td>Summary of AIC and BIC values calculated from different models using monthly maxima data</td>
<td>42</td>
</tr>
<tr>
<td>2.11</td>
<td>Summary of AIC and BIC values calculated from different models using threshold of 0.8m and time span of 3 days</td>
<td>43</td>
</tr>
<tr>
<td>2.12</td>
<td>Summary of 100-year design wave height obtained from various dataset and models</td>
<td>44</td>
</tr>
</tbody>
</table>
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Variations of annual average temperatures in global scale since 1901. In global scale, 2015 was the warmest year on record. Source: Environmental Protection Agency</td>
<td>1</td>
</tr>
<tr>
<td>1.2</td>
<td>Variations of annual average temperatures in the contiguous 48 states. The average surface temperature is rising at the rate of 0.14°F per decade in the U.S. since 1901. Source: Environmental Protection Agency</td>
<td>2</td>
</tr>
<tr>
<td>1.3</td>
<td>Regional variations of annual average temperatures in the contiguous 48 states. North, the West, and Alaska have seen temperatures increase the most, while some parts of the Southeast have experienced little change. Source: Environmental Protection Agency</td>
<td>3</td>
</tr>
<tr>
<td>1.4</td>
<td>Variation of average surface temperature of the world’s oceans since 1880. Source: Environmental Protection Agency</td>
<td>4</td>
</tr>
<tr>
<td>1.5</td>
<td>The average increase rate of absolute sea level is 0.06 inches per year from 1880 to 2013. Since 1993, this value has risen at a rate of 0.11 to 0.14 inches per year. Source: Environmental Protection Agency</td>
<td>5</td>
</tr>
<tr>
<td>1.6</td>
<td>Along much of the U.S. coastline, between 1960 and 2015, relative sea level has risen, particularly, the Mid-Atlantic coast and parts of the Gulf coast. Source: Environmental Protection Agency</td>
<td>6</td>
</tr>
<tr>
<td>2.1</td>
<td>Chesapeake Bay and location of Buoys inside the Bay</td>
<td>11</td>
</tr>
<tr>
<td>2.2</td>
<td>3-Hourly significant wave height (SWH) for Stingray Point location inside Chesapeake Bay for the past 37 years</td>
<td>13</td>
</tr>
<tr>
<td>2.3</td>
<td>Comparison between SWAN and buoy data for year 2012 at (a) Potomac (b) Stingray Point</td>
<td>13</td>
</tr>
<tr>
<td>2.4</td>
<td>Error estimation of the model using correlation coefficient (R) for year 2012 at (a) Potomac (b) Stingray Point</td>
<td>14</td>
</tr>
<tr>
<td>2.5</td>
<td>EOF analysis of of daily-averaged SWHs and extraction of dominated modes of spatial variability (a) mode 1 (b) mode 2 (c) mode 3. Mode 1 accounts for more than 90% of spatial variability inside the Chesapeake Bay</td>
<td>16</td>
</tr>
<tr>
<td>2.6</td>
<td>EOF analysis of of daily-averaged SWHs and extraction of dominated modes of temporal variability (a) mode 1 (b) mode 2 (c) mode 3. Seasonal variability of SWHs is observed from Mode 1. Non-winter seasons are shown using a red arrow</td>
<td>17</td>
</tr>
<tr>
<td>2.7</td>
<td>Detection of significant storm events inside Chesapeake Bay by EOF analysis</td>
<td>18</td>
</tr>
<tr>
<td>2.8</td>
<td>(a) Decadal increases in winter average and annual maxima SWHs (b) Rate of increase of the winter average and annual maxima SWHs</td>
<td>19</td>
</tr>
<tr>
<td>2.9</td>
<td>Comparison of numbers and magnitude of independent storms for the periods 1979-1997 and 1998-2015, documenting the shift in the wave climate to higher waves (a) number of distributions for a range of SWHs (b) empirical cumulative distribution function</td>
<td>21</td>
</tr>
<tr>
<td>2.10</td>
<td>99.5 percentile of independent storms (m) during periods (a) 1979-1997 (b) 1998-2015 (c) difference of two periods. Results show that except lower reach, the Bay experiences a slight increase in extreme wave heights</td>
<td>23</td>
</tr>
</tbody>
</table>
2.11 Threshold selection using (a) parameter stability plot (b) mean residual life plot.

2.12 (a) Number of storm events in which the SWH exceeded a threshold of 1m per calendar month (b) Year day of exceedances above the threshold (dots), annual maxima (circles) and the five largest storms per year (asterisks), illustrating the seasonality of the extreme wave climate of Chesapeake Bay.

2.13 Diagnostic plots from fitting the GEV df to annual maximum (left panel) and monthly maximum (right panel) SWHs (a,d) Density plots of empirical data and fitted GEV df (b,e) Quantile quantile plot (c,f) Return level plot with 95% confidence intervals.

2.14 Diagnostic plots from fitting the GP distribution function to independent storms (a) Density plot of empirical data and fitted GP distribution function (b) Quantile quantile plot (c) Return level plot with 95% confidence intervals.

2.15 Comparison of return levels determined using annual maxima, monthly maxima and POT.

2.16 Q-Q plots derived from (a) GEV (b) Weibull (c) Gamma (d) Log-normal (e) Gumbel distribution functions.

2.17 Q-Q plots derived from (a) GEV (b) Weibull (c) Gamma (d) Log-normal (e) Gumbel distribution functions.

2.18 Q-Q plots derived from (a) GP (b) Gamma (c) Log-normal distribution functions.

2.19 Contours of 100 years return period design wave height (m) determined using (a) Gamma (b) GEV (annual maxima) (c) GP distribution functions (u= 1m, ∆t = 3 days) inside Chesapeake Bay.

3.1 (a) Bathymetry in the Changjiang Estuary; (b) The Changjiang Estuary and the locations of the north passage, two large-scale jetty-spur structures, and nine stations where velocity, salinity, and SSC data are collected.

3.2 Time series of (A) velocity (m/s), (B) salinity (psu) and (C) logarithm of SSC (kg/m³) on August 12, 2012 (Neap tide) from 7:30 am at (a) S3, (b) S4, (c) S6, (d) S8 and (e) S9. Positive values represent flood currents and negative values indicate ebb currents.

3.3 Time series of (A) velocity (m/s), (B) salinity (psu) and (C) logarithm of SSC (kg/m³) on August 17, 2012 (Spring tide) from 5:30 am at (a) S4, (b) S6, (c) S8, (d) S9. Positive values represent flood currents and negative values indicate ebb currents.

3.4 Decomposition of sediment fluxes (kg/m²s) on August 12, 2012 (Neap tide) (a) S1, (b) S3, (c) S4, (d) S6, (e) S8 and (f) S9. Positive values show seaward sediment fluxes and negative values indicate landward sediment fluxes.

3.5 Decomposition of sediment fluxes (kg/m²s) on August 17, 2012 (Spring tide) (a) S1, (b) S3, (c) S4, (d) S6 (e) S8 and (f) S9. Positive values show seaward sediment fluxes and negative values indicate landward sediment fluxes.

3.6 Net sediment transport flux (kg/m²s) during (a) Neap (b) Spring tide. The sediment transport in the passage is dominated by the advective fluxes.

3.7 Time series of eddy viscosities (m²/s) (A) with and (B) without sediment effects and (C) eddy viscosity anomaly on August 12, 2012 (Neap tide) at (a) S3, (b) S4, (c) S6, (d) S8 and (e) S9.
3.8 Time series of eddy viscosities ($m^2/s$) (A) with and (B) without sediment effects and (C) eddy viscosity anomaly on August 17, 2012 (Spring tide) at
(a) S3, (b) S4, (c) S6, (d) S8 and (e) S9. ................. 67
3.9 The along-channel tide-averaged SSC ($kg/m^3$) during (a) neap and (b) spring tides. The highest SSC is located at the middle reach of the north passage
(S3~S6). ......................................................... 69
3.10 The along-channel tide-averaged salinity ($psu$) during (a) neap and (b) spring tides. Turbidity Maximum is located at the middle reach of the north passage
(S3~S6). .......................................................... 70
3.11 Time series of (A) velocity ($m/s$), (B) logarithm of SSC ($kg/m^3$) and (C) bed shear stress ($Pa$) during neap tide at (a) S3, (b) S4, (c) S6, (d) S8 and (e) S9.
The dashed lines show the critical shear stress for erosion. The shaded areas indicate the time when the bed shear stress is small while the SSC is high. 72
3.12 Time series of (A) velocity ($m/s$), (B) logarithm of SSC ($kg/m^3$) and (C) bed shear stress ($Pa$) during spring tide at (a) S3, (b) S4, (c) S6, (d) S8 and (e) S9. The dashed lines show the critical shear stress for erosion. The shaded areas indicate the time when the bed shear stress is small while the SSC is high. 73
CHAPTER 1

INTRODUCTION

There is a general agreement among the scientific community that the earth’s climate is warming and this increasing trend is largely human-induced. In global scale, 2015 was the warmest year on record and 2006–2015 was the warmest decade on record since thermometer-based observations began [1] (Fig. 1.1).

FIG. 1.1: Variations of annual average temperatures in global scale since 1901. In global scale, 2015 was the warmest year on record. Source: Environmental Protection Agency.

The average surface temperature is rising at the rate of 0.15°F per decade since 1901, similar to the rate of warming within the contiguous 48 states which is 0.14°F per decade [1] (Fig. 1.2).
FIG. 1.2: Variations of annual average temperatures in the contiguous 48 states. The average surface temperature is rising at the rate of 0.14°F per decade in the U.S. since 1901. Source: Environmental Protection Agency.

However, since the late 1970s, the United States has warmed faster than the global rate [2]. In the past century, some parts of the United States have experienced more warming than others. For example, the North, the West, and Alaska have seen temperatures increase the most, while some parts of the Southeast have experienced little change (Fig. 1.3).
FIG. 1.3: Regional variations of annual average temperatures in the contiguous 48 states. North, the West, and Alaska have seen temperatures increase the most, while some parts of the Southeast have experienced little change. Source: Environmental Protection Agency.

In the past decades, increasing global temperature resulted in rise of mean global sea surface temperature by 0.1 °F per decade, between 1880 and 2015. From 1901 through 2015, temperature rose at an average rate of 0.13 °F per decade (Fig. 1.4). It has been consistently higher during the past three decades than at any other time since reliable observations began in 1880 (Fig. 1.4). Much of this heat remains in the top 700 meters of the ocean, but the increasing temperature gradient, between ocean layers is predicted to
influence currents and affect ocean circulation [2].

FIG. 1.4: Variation of average surface temperature of the world’s oceans since 1880. Source: Environmental Protection Agency.

Sea level rise is another indicator of climate change. Global average sea level increased throughout the past century, and the rate of change has accelerated in recent years [1]. The average increase rate of absolute sea level is 0.06 inches per year from 1880 to 2013. Since 1993, this value has risen at a rate of 0.11 to 0.14 inches per year (Fig. 1.5). Along much of the U.S. coastline, between 1960 and 2015, relative sea level has risen, particularly, the Mid-Atlantic coast and parts of the Gulf coast, where some stations registered increases of more than 8 inches (Fig. 1.6). There are a lot of recent studies of sea level rise in the Chesapeake Bay and the Atlantic coast, showing that sea level rise in the Bay is 2-3 times faster than global sea level rise [3, 4, 5, 6]. Land subsidence (sinking) and climatic changes in ocean currents such as weakening of the Gulf Stream are some main
reasons associated with that. Despite agreement about the nature of climate change, there are many concerns among coastal communities about potential impacts of global warming on sea level rise, erosion, and the frequency and intensity of coastal storms which play significant roles in protection of coastal communities from coastal hazards. For example, because sea level is rising, waves and storms today can cause more erosion and more flooding than in the past (even if SWH does not change much), and the problem will get worse in the future.

FIG. 1.5: The average increase rate of absolute sea level is 0.06 inches per year from 1880 to 2013. Since 1993, this value has risen at a rate of 0.11 to 0.14 inches per year. Source: Environmental Protection Agency.

Natural and man-made processes, depending on their scale, can impose dramatic changes on the environment. Scientists are responsible to identify and assess the results of such processes on the environment and to predict the likelihood of future changes as
accurately as possible in order to prevent or minimize their adverse impacts. For example, understanding the long-term trends of extreme waves are essential to adequately design, manage and protect man-made infrastructure near coastlines. Recent studies of wave climate confirm significant changes in their intensity and frequency on a global scale.

FIG. 1.6: Along much of the U.S. coastline, between 1960 and 2015, relative sea level has risen, particularly, the Mid-Atlantic coast and parts of the Gulf coast. Source: Environmental Protection Agency.

Reviewing previous research on wave heights in areas such as the Chesapeake Bay reveals a scientific gap in wave characterization primarily due to lack of reliable long-term data. In the second chapter of this research some concerns associated with analysis of extreme wave heights are addressed and temporal and spatial variability of significant wave
heights in the bay are studied by means of Empirical Orthogonal Function (EOF). While in
some estuaries such as the Chesapeake Bay, combination of sea level rise and extreme
waves have important roles on moderating or aggravating natural hazards and erosion risks
that are expected to increase with climate change, in some other estuaries such as
Changjiang Estuary, other physical processes such as tide plays a significant role on
sediment transport. In the third chapter, the impacts of construction of Deep-water
Navigation Channel (DNC) on Changjiang Estuary are analyzed using field measurements
and data analysis. This research provides new insights regarding suspended sediment
dynamics in the estuary and possible sources of sediment in the navigational channel.
CHAPTER 2

STATISTICAL ANALYSIS OF WAVES IN CHESAPEAKE BAY

2.1 INTRODUCTION

Coastal regions have been subjected to vast investments in infrastructure and coastal constructions. Design of coastal structures requires a reliable estimate of characteristic extreme wave heights [7], which is a key element in preventing coastal hazards and substantial economic loss [8]. To find the design wave heights, extreme value analysis (EVA) of significant wave height is always performed. EVA has broad applications in many disciplines such as structural and coastal engineering, weather and climate and finance and traffic prediction. The theory of EVA has been studied by many researchers [9] [10] [11] [12] [13] [14] [15] [16] [17] [18] [19] [20]. Its applications on wave climate analysis were presented by Goda [21], Mathiesen et al. [22], and Teena et al. [8]. The purpose of extreme wave height analysis is to determine the long-term variability of significant wave height through implementations of distribution functions and quantile functions as well as extrapolation of historical data [23] [24] [25] [26] [8] [21] [27] [28] [29] [30] [31].

After the selection of the distribution function, it is important to choose a proper fitting method for determining the unknown parameters of the distribution function. The common fitting methods include maximum likelihood estimate (MLE), generalized maximum likelihood estimate (GMLE), the method of moments (MOM), probability weighted moment (PWM), least square method (LSM), Bayesian, and L-moments [10]. Each of these methods have their own merits and demerits. For example, it has been
shown that for small sample data, MLE might not give a good estimate of parameters and L-moment could be used instead. MOM quantile estimators have smaller root mean square error for specific range of shape parameter values than L-moment and MLE [32]. More detailed information regarding the estimators can be found in Martins et al. [32], Smith [33], Madsen and Rosbjerg [34], Wang [35], and Mathiesen et al. [22].

To reveal spatial and temporal variabilities of extreme wave heights, statistical analysis of long-term wave climate data could be performed. For example, Empirical Orthogonal Function (EOF) analysis can reveal useful information regarding possible spatial patterns of variability within the data and how they change with time. EOF analysis has been widely used in oceanography to study major modes of climate variability such as the El Nino/Southern Oscillation (ENSO) [36, 37, 38], or in coastal engineering [39] to identify spreading and seasonal variability in shoreline and slope data. Another example is the study of wave height changing trends by means of regression analysis. Recent studies on extreme wave climate in different seas revealed that there was a long-term change in extreme waves [40, 41, 42]. Studies on wave height in the North Atlantic near the coast of England [43, 44] and east coast of U.S. [45, 46] showed that there were increases in wave height generated by extreme storms during the past several decades [47]. Similar results have been reported in other locations such as the west coast of U.S. using measurements from NOAA buoy stations [48, 49, 50, 51, 52] and by analysis of storm intensities and hindcasted wave heights [53].

The Chesapeake Bay has been experiencing significant changes in climate forcing. Due to land subsidence, local sea level rise in the lower Chesapeake Bay is much faster than global sea level rise and its rate approaches 4.54 mm per year. This rate will accelerate and
exceed twice this value. The climate change in the Chesapeake Bay has resulted in an increase in storminess in the last decade. With global warming, this trend is anticipated to strengthen in the 21st century. Rise in sea level and increase in storminess will subsequently change the wave climate in the bay. Due to the lack of reliable long-term wave data, limited studies on wave climate in the Chesapeake Bay have been carried out. However, significant advances in satellite altimeters have made it possible for researchers to use wave models to reproduce the historical wave height using reanalysis technique. Examples of these works can be found in various scientific papers [52, 53, 54, 55, 56, 57, 58, 59, 60]. In this study, the SWAN wave model is applied to reconstruct long-term wave climate on the entire Chesapeake Bay. The objectives of this study are (1) to hindcast significant wave height in the bay during 1979-2015; (2) to examine long term changing trends of wave heights; (3) to identify temporal and spatial variability patterns of wave climate in the bay; (4) to calculate and compare design wave heights using different distribution functions.

2.2 STUDY AREA

The Chesapeake Bay is the largest estuary in the United States with the watershed of 165,000 km² covering parts of six states including Delaware, Maryland, New York, Pennsylvania, Virginia, West Virginia, and the District of Columbia. Although understanding of wave characteristics is essential in many aspects including navigational and design purposes, this knowledge has been limited inside Chesapeake Bay mostly because of scarcity of reliable observational data [61]. The first long term wave monitoring within the bay was conducted by Boon et al. [62, 63]. Recently, a number of Buoy systems were deployed by the National Oceanic and Atmospheric Administrations (NOAA)
Chesapeake Bay Interpretive Buoy System (CBIBS) to gather meteorological, oceanographic, and water-quality data. The program was launched in 2007 and the total number of buoys deployed so far is ten. The locations of these buoys are shown in Fig. 2.1.

These buoys are capable of collecting information on a variety of parameters including significant wave height and period, maximum wave height, and mean wave direction. Data is collected every 10 to 60 minutes depending on the parameter and is accessible through their website (http://buoybay.noaa.gov). Although CBIBS can provide valuable information regarding short-term extreme wave height, long-term analysis of these waves requires employing a wave model to obtain realistic estimates of wave characteristics inside the bay.
2.3 WIND DATA AND MODEL VALIDATION

To hindcast long-term significant wave height in the Chesapeake Bay, 37 years of wind data (1979-2015) was collected through the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) [64, 65]. The CFSR uses a coupled atmosphere-ocean-land surface-sea ice system with advanced data assimilation techniques and an extensive database of meteorological observations to create its products [64, 66]. The original CFSR dataset spans from 1979 to 2010 and the second version of the Climate Forecast System (CFSv2) provides products from 2011 up until now with several improvements over CFSR, such as a higher spatial resolution [65]. Temporal resolution for both models is 6 hours. However, spatial resolution of the CFSv2 is approximately 20 km compared to 38 km for CFSR which is a significant improvement. In this study, the third-generation SWAN wave model is employed to obtain 3-hourly significant wave heights for the past 37 years. The computational grid includes 129 \times 65 cells with mesh size of approximately 2.15 \times 2.75 km. As an example, the simulated significant wave heights (SWHs) for 37 years at Stingray Point are depicted in Fig. 2.2. Seasonal variability of the wave heights can be clearly seen. To evaluate the model performance, the simulated and measured SWHs at two buoy stations in 2012 are compared in Fig. 2.3. The reason of choosing year 2012 for demonstration is because wave climate in the Chesapeake Bay was affected by hurricane Sandy in this year. Apparently, the simulations match reasonably well with the measurements. Particularly, the wave height variations during hurricane Sandy were captured by the model.
FIG. 2.2: 3-Hourly significant wave height (SWH) for Stingray Point location inside Chesapeake Bay for the past 37 years.

FIG. 2.3: comparison between SWAN and buoy data for year 2012 at (a) Potomac (b) Stingray Point.
To quantify the model performance, the correlations between simulations and measurements at Potomac and Stingray Point during 2012 are presented in Fig. 2.4. The coefficients of determination ($R^2$) are 0.71 and 0.65, respectively, indicating that the SWAN model is capable of simulating temporal variations of SWHs with reasonable accuracy.

![FIG. 2.4: Error estimation of the model using correlation coefficient (R) for year 2012 at (a) Potomac (b) Stingray Point](image)

### 2.4 STATISTICAL ANALYSES OF SWHS

#### 2.4.1 EOF analysis

The reconstructed SWHs exhibit temporal and spatial variabilities. In order to reveal their patterns, an empirical orthogonal function (EOF) analysis on daily-averaged SWHs is performed. Like Fourier analysis, the EOF provides an expansion of the original data in a
series of functions that separate the spatial and temporal variations \[67\]. These functions are determined by the correlations within the data set and may suggest certain processes or time scales of change. The idea of EOF analysis is to express the time series data as

\[ Z(x, y, t) = \sum_{k=1}^{N} PC(t) \cdot EOF(x, y) \]  

(2.1)

where \( Z(x, y, t) \) is the original time series as a function of time \( t \) and space \( x, y \), \( EOF(x, y) \) is the eigenfunctions (or vectors) of the correlation matrix of the data, which shows the spatial structures of the major factors that account for the spatial variations of the data, and \( PC(t) \) is the principal component describing the temporal variation of each EOF. The EOFs can be obtained by computing the eigenvalues and eigenvectors of a spatially weighted anomaly covariance matrix of a field and the resulting eigenvalues provide a measure of the percentage variance explained by each mode. The lower-mode EOFs represent large-scale variability and higher-mode EOFs show smaller scales or even sometimes random noises. In this study, EOF analysis is performed using a Matlab package and results for the first three modes are presented in Figs. 2.5 and 2.6 respectively. Figure 2.5 demonstrates the spatial distributions of the first three dominant EOF modes for the entire Chesapeake Bay. The corresponding PCs are presented in Fig. 2.6, in which the values are scaled to the range between -1 and 1 by dividing their maximum values.
FIG. 2.5: EOF analysis of daily-averaged SWHs and extraction of dominated modes of spatial variability (a) mode 1 (b) mode 2 (c) mode 3. Mode 1 accounts for more than 90% of spatial variability inside the Chesapeake Bay.

From the calculated eigenvalues, it can be determined that mode 1 accounts for 91.2% of spatial variability of SWHs. The other modes only contribute to a small part of the signal variance. Clearly, the PC of mode 1 demonstrates a seasonal variability of SWHs, with positive PC in winter season (October-March) and negative PC in summer season. The first EOF mode describes deviation from the mean SWH. Combined with the first PC mode, it can be interpreted that in winter season when PC is positive, the wave heights are generally greater than the mean SWH. While in summer season when PC is negative, the wave heights are generally smaller than the mean SWH. The seasonal
variation of wave climate is typical in coastal regions. From Fig. 2.5 it is also found that the first EOF has the largest value in the lower Chesapeake Bay and the smallest value in the upper bay. It is because the lower bay is more exposed and wave height variations are more significant in this region. Since the other PC modes do not show clear variation patterns, they are not discussed herein.

FIG. 2.6: EOF analysis of of daily-averaged SWHs and extraction of dominated modes of temporal variability (a) mode 1 (b) mode 2 (c) mode 3. Seasonal variability of SWHs is observed from Mode 1. Non-winter seasons are shown using a red arrow.

In the first PC mode in Fig. 2.6 several spikes with large positive PC values can be detected. These anomalies are generally linked with hurricane or tropical storm events.

Table 2.1 shows the names of tropical storms and times of occurrence in the past decade.
Largest PC values are spotted when storms hit the bay as shown in Fig. 2.7. There is a close correlation between occurrence of storms and mode 1 eigenvalues. Therefore, EOF analysis not only is able to identify seasonal variation of SWHs but also could be employed to detect extreme storm events in the bay.

TABLE 2.1: Name and occurrence time of hurricanes and tropical storms inside Chesapeake Bay for the past decade

<table>
<thead>
<tr>
<th>Name</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hurricane Sandy</td>
<td>Oct. 26, 2012</td>
</tr>
<tr>
<td>Hurricane Irene</td>
<td>Aug. 26-28, 2011</td>
</tr>
<tr>
<td>Hurricane Ida</td>
<td>Nov. 10-14, 2009</td>
</tr>
<tr>
<td>Hurricane Hanna</td>
<td>Sep. 6, 2008</td>
</tr>
</tbody>
</table>

FIG. 2.7: Detection of significant storm events inside Chesapeake Bay by EOF analysis
2.4.2 Regression analysis

The aim of this section is to analyze the changing trend of wave height inside the Chesapeake Bay using regression analysis and investigate the shift in wave heights for the past several decades. Stingray Point is selected for this purpose since this point is not far from the mouth of the bay so it can capture extreme wave heights entering the bay. Regression analysis is performed on winter-averaged and annual maxima data derived from SWAN results, which are depicted in Fig. 2.8a.

![Graph of Decadal Increases in Winter Average and Annual Maxima SWHs](image1)

![Graph of Rate of Increase of Winter Average and Annual Maxima SWHs](image2)

**FIG. 2.8:** (a) Decadal increases in winter average and annual maxima SWHs (b) Rate of increase of the winter average and annual maxima SWHs
It is found that extreme wave heights at this station were generally increasing. A higher increasing rate of wave height is obtained when more rigorous extreme evaluation is made. The increasing rate of annual maximum wave heights is much higher than that of winter average (4.1 mm/yr versus 1.4 mm/yr).

To examine the robustness of the regression analysis, sensitivity of the calculated trends are tested with respect to the amount of data included in the analysis. Regression analysis is firstly performed using data from 1979 to 2008, and then rate of increase is computed by adding data annually. This process is repeated until all years are included in the analysis. The computed increasing rates for annual maxima and winter average are presented in Fig. 2.8b. Results show that except year 2011 in which there is a decrease in winter average and a sudden increase in annual maxima, rates of wave height increase are fairly stable regardless of the amount of data used. The decrease in winter average and increase in annual maxima in 2011 can be associated with hurricane Irene which passed through the Chesapeake Bay in August.

Statistical significance test has been used widely in hydrology and coastal engineering [68, 47] to examine the significance of the slope of a regression model. In this study, the statistical significance test is performed on each subset of data to examine whether or not the rates of SWH increases derived from regression analysis are statistically significant. The significance test results in a p-value > 0.05, meaning that for both winter average and annual maxima, rate of increases are not statistically significant.

In order to further examine the progressive increases of waves, more detailed analysis of SWHs is provided using probability distributions of all independent storms. Independent storm is defined by Méndez et al. [40]. In this definition, minimum time span between 2
consecutive storms should be selected such that Poisson process is assumed to be valid.

FIG. 2.9: Comparison of numbers and magnitude of independent storms for the periods 1979-1997 and 1998-2015, documenting the shift in the wave climate to higher waves (a) number of distributions for a range of SWHs (b) empirical cumulative distribution function.

Fig. 2.9a shows the number of independent storms occurred for a range of SWHs during two time periods: The first period is defined from 1979 to 1997 and the second one is from 1998 to 2015. Results show that although the total number of independent storms are higher during 1979-1997 by about 12%, the number of extreme storms with SWH larger
than 1.5m exceeds by 33% during period 1998-2015. More explicit explanation of progressive increases of extreme storms is presented in Fig. 2.9, in which the empirical cumulative distribution functions for the two periods are depicted. Although medians for the two periods are almost the same (0.79m and 0.80m for periods 1979-1997 and 1998-2015, respectively), a 9% increase is observed in 99.5 percentile in the period of 1998-2015, confirming the findings from the regression analysis presented in Fig. 2.8 and demonstrating a slight shift towards higher values of extreme wave heights in the past several decades. It is also shown that there is a consistency between the annual increasing rates of SWHs based on regression analysis and cumulative distribution function analysis.

A more comprehensive study of progressive increases of waves inside Chesapeake Bay is performed by obtaining 99.5 percentile of independent storms during periods 1979-1997 and 1998-2015 for the entire bay, which are presented in Fig. 2.10. Except for the lower bay where a maximum decrease of 0.27m in extreme wave height is observed (Fig. 2.10c), the rest of the bay experiences an average increase of 0.1m and the maximum increase is found to be 0.36m in the central bay. Although these changes are small in terms of intensity, they confirm a slight increase in wave heights during the past several decades.
FIG. 2.10: 99.5 percentile of independent storms (m) during periods (a) 1979-1997 (b) 1998-2015 (c) difference of two periods. Results show that except lower reach, the Bay experiences a slight increase in extreme wave heights.

2.4.3 Extreme value assessment

Prediction of extreme wave heights is essential in many wave-climate related problems such as design of coastal and offshore structures and coastal management where flood and erosion hazards can have dramatic impacts on coastal populations and infrastructure [47]. Traditionally, a 50- or 100-year return period should be applied to extreme value models to obtain the corresponding return levels generated by major storms. The purpose of this section is to obtain design wave heights corresponding to different return periods using various extreme value assessment models, to examine applicability of these models, and to perform sensitivity analysis on extracted data to determine the
uncertainty that comes along with extreme value models.

2.4.3.1 Extreme Value Analysis

In extreme value theory, it has been shown that, for sufficiently long sequences of independent and identically distributed random variables, the maxima of samples of size n, can be fitted into the generalize extreme value (GEV) family of distributions which has the following cumulative distribution function [10]

\[
G(z, \mu, \sigma, \xi) = \begin{cases} 
    \exp\left[-(1 + \xi \frac{z-\mu}{\sigma})^{-1/\xi}\right], & \xi \neq 0 \\
    \exp\left[-\exp\left(-\frac{z-\mu}{\sigma}\right)\right], & \xi = 0
\end{cases}
\] (2.2)

where \(\mu, \sigma\) and \(\xi\) are the location, scale and shape parameters, respectively. The three classes of GEV distribution functions are Gumbel distribution (Type I), Frechet distribution (type II) and Weibull distribution (type III). For \(\xi=0\), Gumbel distribution, for \(\xi<0\), Frechet distribution and for \(\xi>0\) Weibull family of distribution will be obtained, respectively. The return level corresponding to return period \(T\) can be obtained using the following equation

\[
R_T = \begin{cases} 
    \mu - \frac{\sigma}{\xi} \{1 - [-ln(1 - \frac{1}{T})]^{-\xi}\}, & \xi \neq 0 \\
    \mu - \sigma ln[-ln(1 - \frac{1}{T})], & \xi = 0
\end{cases}
\] (2.3)

One major concern with GEV approach is that GEV is often applied to annual maxima data, hence ignores other significant extreme events in each year. Other approaches that can be used to reduce this limitation are block maxima and peak-over-threshold (POT) method. In block maxima approach, the entire data is divided
into non-overlap periods of equal size called block and maximum value in each block is
selected for analysis. An example of block maxima approach is monthly maxima which is
included in this study. In the POT method, a high threshold is selected and extreme value
analysis is performed on all the data above the given threshold. It can be shown that for
sufficiently high threshold, the data can be fitted into the so-called generalized Pareto (GP)
distribution function given by

\[
F(z, \sigma, \xi) = \begin{cases} 
1 - (1 + \xi \frac{z}{\sigma})^{-1/\xi}, & \xi \neq 0 \\
1 - \exp(-\frac{z}{\sigma}), & \xi = 0 
\end{cases}
\] (2.4)

where \( \sigma > 0 \) is the scale parameter and \( \xi \) is the shape parameter of the GP distribution
function. Mazas and Hamm [69] showed that along with GEV and GP distribution
functions, the Gamma distribution function often behaves well in terms of fitting the data.
Therefore, performance of Gamma distribution function is also examined. The cumulative
distribution function of Gamma is given by

\[
F(z, \sigma, \xi) = \frac{\gamma(\xi, z/\sigma)}{\Gamma(\xi)}
\] (2.5)

where \( \Gamma \) is the Gamma function and \( \gamma \) is the lower incomplete gamma function.

### 2.4.3.2 Selection of Threshold Value and Time Span

Two important concerns with POT approach are the selection of the threshold and
the minimum time span \( \Delta t \) that is required to assume the independence of consecutive
storm events. Both threshold value and time span affect the results in terms of frequency
and exceedance estimates [40]. Regarding time span, \( \Delta t \) should be chosen sufficiently long
to guarantee the independency between consecutive storms, and to satisfy the validity of Poisson process. A wide range of $\Delta t$ can be found in the literature [70, 40]. In this section, $\Delta t = 3$ days is selected. Results for $\Delta t = 4, 5$ and 6 days are presented in the discussion section to investigate the sensitivity of time interval on the results. The choice of threshold is important in both block maxima and POT approaches. In block maxima approach, it is common to choose a year, a season, or a month for each block. For a sufficiently long data set, determining an appropriate block length is not generally an issue. In POT approach, the threshold ($u$) should be taken sufficiently high for the distribution function to provide a reasonable estimate. On the other hand, it cannot be too high to produce large variance on the estimated parameters.

The two common approaches for selecting threshold are parameter stability plot and mean residual life plot [71]. In the first approach, the parameter estimates from GP distribution function are plotted against a range of values of $u$ [71]. The parameter estimates should be stable above the threshold at which the GP model becomes valid. In the second approach, $u$ is plotted against the ‘mean excess’, which is defined as the mean of the exceedances of $u$ minus $u$. The plot should be linear above the threshold at which the GP model becomes valid. In this study, a POT package [71] written in R language is employed to determine the threshold. Results are depicted in Fig. 2.11 which suggests that both scale and shape parameters show stable behavior around 1m. Therefore, a threshold of 1m can be considered as a suitable choice for POT analysis. The interpretation of a mean residual life plot is not always easy. As can be seen from Fig. 2.11b, the plots are almost linear around $u = 1$m, and then appear to decrease sharply from $u > 1.1$m. Therefore, a threshold of 1m is chosen to perform POT analysis.
The yearly distribution of storm events with 1m threshold wave height is presented in Fig. 2.12. It can be seen from Fig. 2.12a that more than 75% of storm events occur in the winter season. Fig. 2.12b shows the distribution of independent storms above 1m in year day, in which extreme storm events, annual maxima and 5-largest storms in each year are presented with different symbols. The largest wave heights appear in the later hurricane season (Sep. and Oct.). As detected by EOF analysis, seasonal variation of extreme wave heights is observed.
FIG. 2.12: (a) Number of storm events in which the SWH exceeded a threshold of 1m per calendar month (b) Year day of exceedances above the threshold (dots), annual maxima (circles) and the five largest storms per year (asterisks), illustrating the seasonality of the extreme wave climate of Chesapeake Bay.

The GEV and POT analysis are performed using extRemes 2.0 package [72] designed for weather and climate applications. For GEV analysis, annual and monthly maxima are
extracted from simulated wave height data. The parameter estimation is performed by MLE and L-moments and the results for MLE are shown in Fig. 2.13. The density plots (Fig. 2.13a,d) show good agreement between the empirical density (red line) and that of the fitted GEV distribution function (dashed blue line) for both annual and monthly maxima. Fig. 2.13b,e show Q-Q plots of the empirical data quantiles against those derived from the fitted GEV distribution function. The plots are reasonably straight indicating that the utilization of the GEV distribution function is fulfilled by good approximation. For annual maxima (Fig. 2.13b), a slight deviation from the straight line can be observed. However, this deviation is typical for extreme value analysis because of uncertainties associated with extreme value problems. Finally, Fig. 2.13c,f show the return levels corresponding to different return periods of extreme wave heights for annual and monthly maxima respectively. The points on the graphs (Fig. 2.13c,f) are the estimated return levels from annual and monthly maxima data, respectively. The solid blue lines are the estimated return levels based on the fitted GEV model and the dashed red lines are 95% confidence intervals. For both models, the empirical values fall within the 95% confidence intervals and close to the estimated return level, especially, for the monthly maxima model, showing that both models can provide acceptable values for return levels. More detailed information regarding the return levels using different parameter estimators are presented in table 2.2 and table 2.3 respectively.
FIG. 2.13: Diagnostic plots from fitting the GEV df to annual maximum (left panel) and monthly maximum (right panel) SWHs. (a,d) Density plots of empirical data and fitted GEV df. (b,e) Quantile quantile plot. (c,f) Return level plot with 95% confidence intervals.
Both the plots and tables show that return levels extracted from annual maxima data have higher values compared to those extracted from monthly maxima data. For example, return levels for 10, 25, 50 and 100 year return periods from annual maxima data are 26%, 19%, 14% and 10% higher than those from monthly maxima data. It can be also seen from the tables that there are minor changes in return levels in terms of using

<table>
<thead>
<tr>
<th>Return period (year)</th>
<th>LMoments</th>
<th>MLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1.90</td>
<td>1.89</td>
</tr>
<tr>
<td>25</td>
<td>1.97</td>
<td>1.98</td>
</tr>
<tr>
<td>50</td>
<td>2.04</td>
<td>2.04</td>
</tr>
<tr>
<td>100</td>
<td>2.09</td>
<td>2.09</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Return period (year)</th>
<th>LMoments</th>
<th>MLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1.50</td>
<td>1.50</td>
</tr>
<tr>
<td>25</td>
<td>1.68</td>
<td>1.67</td>
</tr>
<tr>
<td>50</td>
<td>1.8</td>
<td>1.79</td>
</tr>
<tr>
<td>100</td>
<td>1.91</td>
<td>1.90</td>
</tr>
</tbody>
</table>
different parameter estimators. The variation of return level is less than 0.6%, indicating that both estimators can be used for extreme value analysis of wave height.

In the POT analysis, a threshold of 1m and a time span of 3 days are selected, which results in 386 independent storms. The results using MLE estimator is presented in Fig. 2.14. Density plot (Fig. 2.14a) shows a good agreement between the empirical density function (red line) and the fitted GP distribution function (dashed blue line). Similar to GEV model, Q-Q plot (Fig. 2.14b) from GP model is straight indicating that GP distribution function can be used for EVA with good approximation. The empirical points (Fig. 2.14c) are very close to the estimated return levels from GP distribution function showing that it provides good approximation for return levels. Comparisons of return levels using different estimators are shown in table 2.4. Slight differences on return levels are observed using MLE and L-moments estimators.
FIG. 2.14: Diagnostic plots from fitting the GP distribution function to independent storms
(a) Density plot of empirical data and fitted GP distribution function (b) Quantile quantile plot (c) Return level plot with 95% confidence intervals
Comparison of return levels obtained from GEV and POT show that POT and GEV produce almost the same results, especially for higher return periods. For example, for 100 year return period, POT and annual maxima GEV produce the same results, while for monthly maxima GEV model the difference is only 10%. From the above analyses, it can be concluded that both GEV and POT are reliable approaches for estimating design wave heights. More detailed comparisons of these three approaches are presented in Fig. 2.15, in which return levels or design wave heights are plotted against return periods using MLE estimator. The conclusions are the same as what are observed in table 2.2, 2.3 and 2.4.

FIG. 2.15: Comparison of return levels determined using annual maxima, monthly maxima and POT
TABLE 2.4: Return levels calculated using POT analysis (threshold= 1m, \( \Delta t = 3 \) days) and different parameter estimation methods

<table>
<thead>
<tr>
<th>Return period (year)</th>
<th>Return level (m)</th>
<th>LMoments</th>
<th>MLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1.86</td>
<td>1.86</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>2.00</td>
<td>2.01</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>2.05</td>
<td>2.06</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>2.08</td>
<td>2.09</td>
<td></td>
</tr>
</tbody>
</table>

2.5 DISCUSSIONS

The choice of distribution functions, the selection of threshold and time span as well as data length included in the analysis are important in extreme value assessment. Therefore, this section is devoted to perform sensitivity analyses of these parameters to understand the effects of each parameter on the estimation of design wave height.

2.5.1 Threshold and time span

In order to investigate the impacts of threshold wave height and time span on design wave heights, a sensitivity analysis is performed by choosing values of 0.8, 0.9, 1.0, 1.1 and 1.2 m for threshold wave height and 3, 4, 5 and 6 days for time spans. The return levels are calculated using MLE estimator and results for different time spans are shown in table 2.5 through 2.8.
TABLE 2.5: Return levels for time span $\Delta t = 3$ days and various thresholds

<table>
<thead>
<tr>
<th>Return period (year)</th>
<th>Threshold (m) for $\Delta t = 3$ days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.8</td>
</tr>
<tr>
<td>10</td>
<td>1.71</td>
</tr>
<tr>
<td>25</td>
<td>1.91</td>
</tr>
<tr>
<td>50</td>
<td>1.99</td>
</tr>
<tr>
<td>100</td>
<td>2.04</td>
</tr>
</tbody>
</table>

TABLE 2.6: Return levels for time span $\Delta t = 4$ days and various thresholds

<table>
<thead>
<tr>
<th>Return period (year)</th>
<th>Threshold (m) for $\Delta t = 4$ days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.8</td>
</tr>
<tr>
<td>10</td>
<td>1.75</td>
</tr>
<tr>
<td>25</td>
<td>1.94</td>
</tr>
<tr>
<td>50</td>
<td>2.02</td>
</tr>
<tr>
<td>100</td>
<td>2.06</td>
</tr>
</tbody>
</table>
TABLE 2.7: Return levels for time span $\Delta t = 5$ days and various thresholds

<table>
<thead>
<tr>
<th>Return period (year)</th>
<th>Threshold (m) for $\Delta t = 5$ days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.8</td>
</tr>
<tr>
<td>10</td>
<td>1.81</td>
</tr>
<tr>
<td>25</td>
<td>1.98</td>
</tr>
<tr>
<td>50</td>
<td>2.04</td>
</tr>
<tr>
<td>100</td>
<td>2.08</td>
</tr>
</tbody>
</table>

TABLE 2.8: Return levels for time span $\Delta t = 6$ days and various thresholds

<table>
<thead>
<tr>
<th>Return period (year)</th>
<th>Threshold (m) for $\Delta t = 6$ days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.8</td>
</tr>
<tr>
<td>10</td>
<td>1.88</td>
</tr>
<tr>
<td>25</td>
<td>2.02</td>
</tr>
<tr>
<td>50</td>
<td>2.07</td>
</tr>
<tr>
<td>100</td>
<td>2.09</td>
</tr>
</tbody>
</table>

It is shown that design wave height generally increases for different return periods with increasing time span. Another interesting result is that, for a specific time span, higher threshold wave height results in higher return level. Although, the variation rates of return levels are very small, especially for higher return periods.
2.5.2 Distribution functions

In order to evaluate the performance of GEV and GP distribution functions in terms of fitting the data, a comparison is made between GEV distribution functions and Weibull, Gumbel, Gamma, and Log-normal distribution functions by calculating Bayesian Information Criterion (BIC), also known as the Schwarz Criterion \[73\] and Akaike Information Criterion (AIC) \[74\]. BIC minimizes the bias between the fitted model and the unknown true model, which is given by

$$BIC = -2\ln L + k_p\ln N$$ (2.6)

where $L$ is the likelihood of the fit, $N$ is the sample size (number of storm peaks above threshold) and $k_p$ is the number of parameters of the distribution. The AIC which can be inferred as the best compromise between bias and variance \[74\] is given by

$$AIC = 2\ln L + 2k_p$$ (2.7)

The lower value of AIC or BIC indicates a better fit. It is worth noting that the best fit does not necessarily provide the desirable result for design purposes, as selecting a conservative return level seems more reasonable.

In order to perform the goodness of fit test, fitdistrplus \[75\] and extRemes 2.0 packages are employed. fitdistrplus has the capability of using different estimation methods such as MLE to compare the fit of several distributions to the same data set. The first comparison is made among GEV, Weibull, Gumbel, Gamma and Log-normal using annual maxima data. Table 2.9 shows the summary of AIC and BIC values calculated from
different models using MLE.

TABLE 2.9: Summary of AIC and BIC values calculated from different models using annual maxima data

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Model</th>
<th>GEV</th>
<th>Weibull</th>
<th>Gumbel</th>
<th>Gamma</th>
<th>Log-normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>-9.89</td>
<td>-8.24</td>
<td>-8.36</td>
<td>-11.35</td>
<td>-8.91</td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>-4.73</td>
<td>-5.01</td>
<td>-5.13</td>
<td>-8.13</td>
<td>-7.98</td>
<td></td>
</tr>
</tbody>
</table>

It can be seen from table [2.9] that there is a slight difference between AIC and BIC calculated from the models showing that nearly all models are capable of fitting the annual maxima data. However, Gamma distribution function gives the best fit and GEV provides a better fit than Weibull and Gumbel distribution functions. Q-Q plot is employed to qualitatively compare the performance of all models and to check whether or not the actual and model data sets come from a population with the same distribution (Fig. [2.16]). For Gumbel and Weibull distribution functions, Q-Q plots confirm AIC and BIC tests shown in table [2.9] as some points deviate from the straight line. However, for GEV, log-normal, and Gamma distribution functions, the points fall approximately along the reference line indicating that these models provide better fits. Analyses are also performed on monthly maxima data to evaluate the performance of all models (Fig. [2.17]). The results are presented in table [2.10].

For POT analysis, GP distribution function is compared with Gamma, and Log-normal distribution functions and the results of AIC and BIC tests are shown in table
In this analysis, threshold wave height of 0.8 m and time span of 3 days are chosen. Q-Q plots (Fig. 2.18) are also drawn to verify results obtained from AIC and BIC tests.

FIG. 2.16: Q-Q plots derived from (a) GEV (b) Weibull (c) Gamma (d) Log-normal (e) Gumbel distribution functions
FIG. 2.17: Q-Q plots derived from (a) GEV (b) Weibull (c) Gamma (d) Log-normal (e) Gumbel distribution functions
TABLE 2.10: Summary of AIC and BIC values calculated from different models using monthly maxima data

<table>
<thead>
<tr>
<th>Criteria</th>
<th>GEV</th>
<th>Weibull</th>
<th>Gumbel</th>
<th>Gamma</th>
<th>Log-normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>163.52</td>
<td>197.43</td>
<td>171.66</td>
<td>161.82</td>
<td>168.06</td>
</tr>
<tr>
<td>BIC</td>
<td>173.81</td>
<td>205.63</td>
<td>179.86</td>
<td>170.01</td>
<td>172.25</td>
</tr>
</tbody>
</table>

FIG. 2.18: Q-Q plots derived from (a) GP (b) Gamma (c) Log-normal distribution functions
TABLE 2.11: Summary of AIC and BIC values calculated from different models using threshold of 0.8m and time span of 3 days

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Model</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GP</td>
<td>Gamma</td>
<td>Log-normal</td>
</tr>
<tr>
<td>AIC</td>
<td>-568.89</td>
<td>-234.31</td>
<td>-283.85</td>
</tr>
<tr>
<td>BIC</td>
<td>-559.52</td>
<td>-224.94</td>
<td>-274.48</td>
</tr>
</tbody>
</table>

Q-Q plots (Fig. 2.18) suggest that none of distribution functions are suitable for POT analysis except GP distribution function. Kolmogorov-Smirnov test, Chi-square goodness-of-fit test, and Anderson-Darling test are implemented to check if the data used for POT analysis comes from distribution functions presented in this study. Except GP distribution function, all the above-mentioned tests reject the null hypothesis that the data come from such distributions. Therefore, GP distribution function can be considered as a suitable tool for POT analysis of the data.

2.5.3 Length of data used in the analysis

The length of data included in the analysis can also play a significant role in obtaining the proper design wave height. Therefore, a sensitivity analysis is performed in terms of sample duration, by using 10, 19, 28 and 37 year datasets corresponding to the datasets during 1979-88, 1979-97, 1979-2006 and 1979-2015, respectively. The design wave heights with a return period of 100 years are obtained using GEV, Gamma and GP distribution functions.
TABLE 2.12: Summary of 100-year design wave height obtained from various dataset and models

<table>
<thead>
<tr>
<th>Model</th>
<th>Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>GEV-monthly maxima</td>
<td>1.76</td>
</tr>
<tr>
<td>GEV-annual maxima</td>
<td>1.77</td>
</tr>
<tr>
<td>Gamma-monthly maxima</td>
<td>1.85</td>
</tr>
<tr>
<td>Gamma-annual maxima</td>
<td>1.91</td>
</tr>
<tr>
<td>GP (u=1 m, Δt=3 days)</td>
<td>1.90</td>
</tr>
</tbody>
</table>

It can be seen from table 2.12 that longer dataset results in higher design wave height, which contradicts the findings of Mazas and Hamm [69] that shorter dataset produced higher design wave height. This contradiction is mostly due to the property of data being analyzed. Since extreme events are unpredictable, higher design wave height can be obtained in smaller datasets if extreme storm events happen during that time period. In addition, a minor difference (2% maximum difference) between design wave heights obtained from 28- and 37-year dataset is obtained, suggesting that 28 years might be sufficiently long for extreme wave height analysis. The maximum difference intensifies for 10- and 19-year dataset compared to 37-year dataset by 18% and 14%, respectively. Therefore, these datasets can not provide good estimates of design wave height for 100-year return period.

Based on the analyses performed in this study, Gamma , GEV and GP distribution
functions are selected to draw contours of design wave heights with 100-year return period for the entire Chesapeake Bay. The results are shown in Fig. 2.19. The design wave height generally decreases from the lower bay to the upper bay, with design wave height between 1.5-2 m in the upper bay. It increases substantially in the lower bay and reaches up to 3.25 m. Gamma distribution function gives a more conservative estimate of design wave height (Fig. 2.19a) compared to GEV and GP distribution functions (Figs. 2.19b and 2.19c). GP distribution function fails to provide design wave height in shallow areas since its analysis is based on a threshold value that might be greater than the largest waves in those areas.

2.6 SUMMARY

In this research, SWAN wave model was applied to reconstruct the wave climate in the Chesapeake Bay between 1979 and 2015. Statistical analyses including EOF analysis, regression analysis, and extreme value analysis on the simulated long-term significant wave height data were carried out. In the extreme value analysis, both GEV and POT methods were applied to estimate design wave heights. The reliability of these methods was extensively studied. The effects of key parameters such as threshold value, time span as well as data length on the design wave heights were also evaluated.
FIG. 2.19: Contours of 100 years return period design wave height (m) determined using (a) Gamma (b) GEV (annual maxima) (c) GP distribution functions ($u = 1$ m, $\Delta t = 3$ days) inside Chesapeake Bay
CHAPTER 3

SEDIMENT PROCESSES IN THE CHANGJIANG ESTUARY

3.1 INTRODUCTION

Erosion and sediment processes in natural systems, depending on their scales, often exhibit complicated behavior in response to environment. This complexity can be intensified dramatically, when it is accompanied by human activities. Changjiang Estuary is a great example of such a natural system. Recent development and construction of coastal structures in the estuary have greatly complicated suspended sediment dynamics, which is also influenced by the interplay between tides and river inflow.

Due to the importance of Changjiang Estuary on navigation and local economy, a great number of studies on the estuary have been conducted in the past few decades, among which sediment resuspension, deposition, and transport have always been the major concerns [76]. For instance, Milliman et al. [77] performed extensive field studies on sediment deposition in the Changjiang Estuary, indicated that the north channel of the south branch was mostly responsible for transporting sediments to the ocean. Sediment transport was directly related to river stage, but tidal phase also played a significant role. Shi et al. [78] studied sediment resuspension in the Changjiang Estuary using field measurements. It was shown that the maximum value of suspended sediment concentration (SSC) occurred slightly after slack water when the diffusion of suspended sediment was the strongest. Shi [79] used measured current velocity, salinity, and SSC during spring, moderate and neap tides at two ends of north passage of Changjiang Estuary to reveal the
dominant mechanisms responsible for turbidity maximum. Chen et al. [80] measured and analyzed in Changjiang Estuary for different periods. Their results suggested that averaged SSCs are increasing from landward to seaward and the fine suspended sediment particles show a seasonal and spring-neap tide variations. Shi [76] revealed two mechanisms responsible for suspended sediment dynamics in the Changjiang Estuary: near-bed impulsive resuspension and transport processes driven by fine sediment-induced plumes. It was concluded that both tidal acceleration and deceleration had significant impacts on the concentration profiles of fine sediment in the south passage of the Changjiang Estuary.

Recent studies have been focused on the effects of coastal structures on sediment dynamics. In order to improve the deep-water navigational channel (DNC) and alleviate navigation condition, two long jetties and tens of jetty-attached spurs were constructed along the north passage of the Changjiang Estuary (Fig. 3.1). These jetties extended 50 km long, and significantly changed sediment transport patterns in the local regions. A number of studies have been conducted to investigate these impacts during different stages of construction in the Changjiang Estuary. Du and Yang [81] studied the effects of DNC on erosion and accumulation of Hengsha east shoal and Jiuduan shoal (Fig. 3.1b). According to their findings, DNC played a significant role in the expansion of these shoals. Ma et al. [82] studied the temporal and spatial variations of the sediment deposition rate in the north passage. It was found that sediment deposition in the north passage experienced annual and seasonal variations, and it was greatly influenced by human activities. They calculated the annually averaged sediment depositions in the channel before and after the extension of jetty-spur structures. Their calculations showed that the main deposition region migrated from the lower section to upper section of the channel. Liu et al. [83] identified severe
deposition in the DNC as one of the most challenging problems in the Changjiang Estuary. They investigated the effects of residual currents and sediment flux on sediment deposition in the channel and showed that the maximum salinity gradient at the peak flood current resulted in high sedimentation rates in this section of the estuary. Song et al. [84] studied suspended sediment transport processes in the DNC over spring and neap tidal cycles. It was shown that fluvial flows play a significant role in offshore sediment transport, however, onshore transport is induced by tidal-pumping effects on spring and shear effects on neap tides. Ge et al. [85] used satellite data and finite volume coastal ocean model (FVCOM) to estimate the near-bed critical shear stress in the clay-dominated bed region. Their results showed that lateral water exchange between channels and shoals occurred during spring flood tide leads to a broader high SSC area in Changjiang Estuary. Li et al. [86] indicated that stratification in the Estuary controlled by advection of salt wedge and the landward sediment transport in the lower layers might be responsible for sediment trapping. Therefore, this mechanism should be further investigated in future studies.

Although these studies have greatly increased our knowledge on sediment properties and processes in the estuary, more research still needs to be conducted due to the complexity of the problem. The objectives of the research are to study sediment transport patterns in the summer time, when sediment supply from the Changjiang River is abundant, to find out the likely sources of suspended sediment in the navigational channel, and to discuss the effects of suspended sediments on enhanced stratification of the water column in the DNC, which would affect net sediment flux and sediment deposition in the channel. Field measurements on water level variations, tidal currents and SSCs at 9 stations in the north passage of the estuary are collected and analyzed.
FIG. 3.1: (a) Bathymetry in the Changjiang Estuary; (b) The Changjiang Estuary and the locations of the north passage, two large-scale jetty-spur structures, and nine stations where velocity, salinity, and SSC data are collected.
3.2 STUDY AREA AND FIELD SURVEYS

Changjiang Estuary is a partially mixed estuary located in a mesotidal coast of east China, which has four distributaries separated by islands and shoals (Fig. 3.1). It is divided into two branches by Chongming Island. The south branch is further split into two channels by Changxing and Hengsha Islands. The Jiuduan shoal located at the south channel divides the channel into south and north passages. We focus our studies in the north passage of the Changjiang Estuary (Fig. 3.1), where the DNC is located. The hydrodynamics and sediment dynamics in the north passage are very complicated due to the interplay between river discharge and tides. The tide is dominantly semidiurnal, with the averaged tidal range of 2.84 m on the east side of Jiuduan Shoal. The Changjiang River provides most of the freshwater input, with the average annual runoff of $9.24 \times 10^{11}$ $m^3$. The river discharge has a strong seasonal variation. Approximately 70% of the runoff occurs in the flood season from May to October, and only 30% occurs in the rest of the year [84]. The river discharge in the summer time is abundant and peaks in July with a monthly-averaged discharge of 50,500 $m^3/s$. Saltwater from the ocean meets the freshwater from the Changjiang River in the north passage, forming the saltwater intrusion front, which plays an important role in the formation of turbidity maxima and severe sediment deposition in the DNC. The hydrodynamics and suspended sediment dynamics in the north passage have also been influenced by human activities in the past decade. Two long jetties and tens of jetty-attached spurs were constructed along the north passage from Aug. 1998 to March 2005 to stabilize the navigational channel. The length of the jetty-spur system is about 50 km and the total length of two jetties is around 100 km, being the
longest jetties in the world. Dredging was carried out frequently to maintain the water depth in the channel. These activities greatly changed the suspended sediment dynamics in the north passage.

The sediments in the north passage are exclusively silt and clay. The median size of the bed sediments ranges between 0.056 and 0.010 mm with the mode between 0.063 and 0.008 mm [87]. The median size of the suspended sediment varies between 0.004 and 0.009 mm [87]. To study suspended sediment dynamics in the north passage after the construction of jetty-spur structures, two field surveys were conducted on August 12 (from 7:30 am) and 17 (from 5:30 am) of 2012 representing neap and spring tide conditions, respectively. The sampling data include water level, current, salinity, and SSC profiles at half-hour intervals. Field measurements were carried out in calm conditions. As a result, wind and wave effects were negligible and therefore, they were not measured in this study. The measurements were performed at 9 stations, which are shown in Fig. 3.1. The duration of the measurements varies from 26 to 35.5 hours at different stations. All the data were measured at six levels with different relative water depth (surface, 0.2H, 0.4H, 0.6H, 0.8H, and bottom, where H is the total water depth). Tidal currents were measured by ADCPs and current meters. Salinity was measured by OBS-3A sensors. SSC was obtained by analyzing water samples in the laboratory. It should be noted that the salinity at S2, S5 and S7, SSCs at S2 and S7 and tidal current data at S5 for the neap tide, as well as salinity, SSC and tidal current data at S2, S5 and S7 for the spring tide were missing and therefore are not presented in this study. To facilitate the discussions, we roughly divide the passage into three sections: the upper reach covering S1∼S2, the middle reach having S3∼S6 and the lower reach including S7∼S9.
3.3 RESULTS

3.3.1 Flood-ebb asymmetry and fortnightly variability

In order to evaluate suspended sediment dynamics in the north passage of the estuary, time series of current, salinity, and SSC at several stations for neap and spring tide conditions are plotted in Figs. 3.2 and 3.3 respectively. To better visualize the distribution of SSC within the water column, values of SSCs are shown in logarithmic scale. Notice that the ebb current is directing to the ocean with negative velocities in the figures, while the flood current is toward the river with positive velocities.

The first set of data was collected during neap tide (Fig. 3.2). The maximum tidal range is about 2.5 m, indicative of a mesotidal condition. The tide is semi-diurnal and inequality can be observed at all stations. Tidal current velocity varies from 0.47 to 1.8 m/s. The maximum ebb current velocity is 1.8 m/s at S2 and S4, and maximum flood current velocity is 1.59 m/s at S9. In the upper and middle reaches of the channel (S1 to S4), the vertical distribution of flood current is relatively homogeneous, while the ebb current is more vertically sheared (Figs. 3.2a,b). In the lower reach, the velocity profiles become more sheared during both ebb and flood (Fig. 3.2d). Salinity variations at S3 and S4 indicate that the saltwater intrusion during neap tide can influence the middle and upper reaches of the north passage. The highest SSCs are found to be coincident with the highest salinity in the water column due to the fact that suspended sediments are trapped by the saltwater intrusion front. In the lower reach, salinity generally increases during flood and decreases during ebb with high salinity at slack water. At S1, sediment elevates at peak ebbs and ebb slacks. The maximum SSC is 0.252 kg/m$^3$ and the vertically and
time-averaged SSC (VTASSC) is 0.0795 kg/m$^3$. At S3, the sediment is suspended during both ebb and flood and the corresponding values for the maximum and VTASSC are 7.41 and 0.3678 kg/m$^3$, respectively. At S4, the SSC is higher during flood and the maximum and VTASSC are 4.59 and 0.3707 kg/m$^3$, respectively. At S5, the SSC reaches its highest value during flood. The maximum and VTASSC are 14.7 and 0.6330 kg/m$^3$, respectively. SSC then decreases downstream of the channel toward S9 where the maximum and VTASSC are 1.11 and 0.1257 kg/m$^3$ (Fig. 3.2).

In order to have a better understanding of sediment transport processes during spring-neap tidal cycle, the second set of data was collected on August 17 of 2012 representing a spring tide condition. During this time period, the tidal range is between 3.6 and 4.6 m. The distributions of tidal velocity, salinity, and SSC are depicted in Fig. 3.3. Contours of flood and ebb velocities (Fig. 3.3A) reveal that at all stations, ebb current is stronger than flood current indicative of an ebb dominant condition. The maximum ebb current happens at S8 with the magnitude of 3.58 m/s whereas the maximum flood current occurs at S4 with the value of 2.14 m/s. The ebb currents are more sheared compared to flood currents (see Figs. 3.3a,b,c). The temporal variations of salinity have similar patterns as those during neap. Saltwater intrusion occurs during flood, creating strong stratification in the water column. At S4, the temporal variations of SSC are consistent with salinity having the peak values at flood. The maximum and VTASSC at S4 are 21.08 and 0.9457 kg/m$^3$, respectively, which are much higher than those during neap. The SSC at S6 is higher with the highest VTASSC of 1.2712 kg/m$^3$. Similar to the neap tide condition, SSC generally decreases toward the ocean. For example, the maximum and VTASSC at S9 are 2.65 and 0.3884 kg/m$^3$, respectively.
In general, SSCs during spring tide are much higher than during neap tide. For example, VTASSCs at S6, S8 and S9 during spring are more than 3 times larger than those during neap. However, the spatial distributions of the SSCs are quite similar in both conditions, with lower values in the upper and lower reaches of the channel and higher concentrations in the middle reach of the channel.
FIG. 3.2: Time series of (A) velocity (m/s), (B) salinity (psu) and (C) logarithm of SSC (kg/m³) on August 12, 2012 (Neap tide) from 7:30 am at (a) S3, (b) S4, (c) S6, (d) S8 and (e) S9. Positive values represent flood currents and negative values indicate ebb currents.
FIG. 3.3: Time series of (A) velocity ($m/s$), (B) salinity ($psu$) and (C) logarithm of SSC ($kg/m^3$) on August 17, 2012 (Spring tide) from 5:30 am at (a) S4, (b) S6, (c) S8, (d) S9. Positive values represent flood currents and negative values indicate ebb currents.

3.3.2 Sediment transport fluxes

In order to investigate suspended sediment transport processes in the channel and estimate net sediment transport rate in the summer time, sediment transport fluxes are calculated at all stations using the method described in Gong et al. [88]. Since the data was measured at six relative elevations, linear interpolation is used to obtain data at fixed depths. The sediment transport flux at each vertical layer is decomposed into two parts as
follows

\[
\bar{u}s = (\bar{u})(\bar{s}) + u_t s_t
\]  

(3.1)

Where \( u \) is the velocity in \( x \) or \( y \) direction, \( s \) is the SSC, the over bar represents the time averaging operator over a 25-hour period and the subscript \( t \) denotes tidal variations. The term on the left hand side of Eq. (3.1) represents the total sediment transport flux. The first term on the right hand side represents the mean advective flux (residual flux), and the second term is the flux associated with tidal dispersion which is called tidal flux \[89, 90\].

The coordinate reference for calculating and analyzing the data is Cartesian coordinate system and it is assumed that, for negative values of \( x \), the flow is toward the land (flood condition) and for positive values of \( x \), the flow is toward the sea (ebb condition). Values associated with each term are calculated and the results for both neap and spring tides are presented and discussed in this section.

The tide-averaged residual and net sediment fluxes at different stations during neap tide show that net sediment transport is generally seaward (Figs. 3.4a,b,c,d). Exceptions are at S8 and S9, where interactions between river discharge and tidal flow produce a two-layer estuarine circulation (Figs. 3.4e,f). As a result, a landward total sediment flux in the lower layer and a seaward total sediment flux in the upper layer of the water column appear at S8 (Fig. 3.4e). The magnitude of the landward total flux is even larger than that of the seaward total flux, indicating a landward net sediment transport at this station. Same pattern can also be observed at S9 (Fig. 3.4f). In the upper and middle reaches of the north passage (i.e. S1 to S7), the advective flux plays a major role in total sediment transport due to the asymmetry of the tidal flow. In the lower reach (i.e. S8 and S9), tidal
flux becomes increasingly more important, especially in the lower water column where a net landward residual flow appears. The sediment fluxes at S1, S3, S4, S6, S8 and S9 during spring tide are presented in Fig. 3.5. Due to higher SSC during spring, the total sediment fluxes are larger than during neap. It is shown that the net sediment transport at S1 to S8 is unidirectionally seaward with lower magnitude at the top and higher magnitude near the bottom (Figs. 3.5a,b,c,d,e). The total flux has the same pattern. The total flux at the bottom of S8 (Fig. 3.5e) is about 4 times larger than that of S1 (Fig. 3.5a). At S9, a two-layer sediment transport pattern still appears with a landward total flux in the lower layer and a seaward total flux in the upper layer (Fig. 3.5f). Similar to neap tide condition, the total sediment flux is primarily contributed by the advective component from S1 to S7 (Figs. 3.5a,b,c,d,e). Advective flux is responsible for 70~100% of the total sediment transport at these stations. The tidal flux becomes more important in the lower reach of the north passage at S8 and S9 (Figs. 3.5e and f, respectively) and reduces the role of advective flux by 40~60%.
FIG. 3.4: Decomposition of sediment fluxes \((kg/m^2s)\) on August 12, 2012 (Neap tide) (a) S1, (b) S3, (c) S4, (d) S6, (e) S8 and (f) S9. Positive values show seaward sediment fluxes and negative values indicate landward sediment fluxes.
FIG. 3.5: Decomposition of sediment fluxes \((kg/m^2s)\) on August 17, 2012 (spring tide) (a) S1, (b) S3, (c) S4, (d) S6 (e) S8 and (f) S9. Positive values show seaward sediment fluxes and negative values indicate landward sediment fluxes.

The total sediment fluxes at the surface and bottom layers during neap and spring are shown in Figs. 3.6a and 3.6b respectively. The net sediment fluxes are generally
seaward with larger magnitudes during spring and smaller values during neap. Only at S8 and S9 during the neap tide (Fig. 3.6a) and S9 (Fig. 3.6b) during spring tide, direction of net sediment flux is landward at the bottom. The magnitude of net sediment flux in the middle reach of the channel is considerably larger compared to upper and lower reaches, especially in the bottom layer. This is mainly because of the existence of high SSC in the middle reach of the channel.

**FIG. 3.6:** Net sediment transport flux (kg/m²s) during (a) Neap (b) Spring tide. The sediment transport in the passage is dominated by the advective fluxes.

### 3.4 DISCUSSIONS

#### 3.4.1 Sediment-induced stratification

Suspended sediment in the water column usually has the highest concentration near the bed and the smallest concentration at the surface, producing a vertical gradient of SSC. Various studies have demonstrated that the vertical gradient of suspended sediment concentration may reduce turbulence intensity and stratify water column \[91, 92, 93\]. With
the reduction of turbulence intensity, more severe sediment deposition is expected. Geyer [91] found that the reduction in turbulence due to sediment-induced stratification enhances the trapping of suspended sediments and promotes the formation of estuarine turbidity maximum (ETM). In Changjiang Estuary, the effects of sediment-induced stratification on sediment deposition as well as sediment flux have received less attention.

To examine the sediment-induced stratification, the turbulent eddy diffusivity in the water column is calculated using a formula given by Munk and Anderson [94] as follows

\[ k = k_0 \left( 1 + \frac{10}{3} Ri \right)^{-1.5} \]  

(3.2)

Where \( k_0 \) is the turbulent diffusivity for unstratified water column and \( Ri \) is the Richardson number. In the absence of stratification, turbulence in an estuary is characteristic of open channel flow, for which the vertical mixing can be described by a parabolic eddy diffusivity [91].

\[ k_0 = \beta \kappa u_* z \left( 1 - \frac{z}{h_0} \right) \]  

(3.3)

Where \( \beta \approx 1 \) is a proportionality coefficient between eddy viscosity and diffusivity, \( \kappa = 0.41 \) is Von Karman constant, \( u_* = (\tau_b / \rho)^{0.5} \) is the friction velocity, where \( \tau_b \) is the bottom stress, \( \rho \) is water density, \( z \) is the elevation above the bed, and \( h_0 \) is the water depth. The Richardson number, which is the ratio of buoyancy to shear production, signifies the degree of stratification and mixing in estuaries. Typical values of \( Ri \) in stratified estuaries vary from 0.5 to 10 [91]. \( Ri = 0.25 \) is considered as the threshold to separate two different turbulent regimes: strong mixing for \( Ri < 0.25 \) and weak mixing for \( Ri > 0.25 \) [95]. The \( Ri \)
can be calculated by

\[ Ri = -\frac{g}{\rho} \frac{\partial \rho}{\partial z} \left( \frac{\partial u}{\partial z} \right)^2 \]  

(3.4)

Where \( g \) is gravitational acceleration, \( \rho \) is density of water and \( u \) is current velocity at different depths. Very similar to water-sediment density mixture [96], density of water can be calculated considering salinity and SSC in the water column as follows [92].

\[ \rho(S,c) = \rho_w(S) + \left( 1 - \frac{\rho_w(S)}{\rho_s} \right) c \]  

(3.5)

Where \( \rho_w(S) \) is the density of water due to salinity only, \( \rho_s \) is sediment density (2650 kg/m\(^3\)), \( c \) is mass sediment concentration (kg/m\(^3\)) and \( \rho(S,c) \) is the density of water due to both salinity and sediment. The effects of suspended sediment on stratification and mixing are investigated by calculating \( k \) with and without considering concentration of sediment particles in the water column.

The calculated eddy viscosities for neap and spring tide conditions are presented in Fig. 3.7 and 3.8 respectively, from which we can clearly see the flood-ebb asymmetry and fortnightly variability of turbulent mixing and stratification. The eddy viscosities are typically 2~3 times larger during spring than those during neap, indicating that much stronger mixing occurs during spring. The eddy viscosities at ebb are much larger than those at flood because of stronger ebb current and weaker saltwater-induced stratification. During flood, saltwater can intrude to the upper reach of the north passage, producing strong stratification and less mixing in the navigational channel (Fig. 3.2 and 3.3). There is also along-channel variability of the turbulent mixing and stratification. Generally, the
eddy viscosities in the upper reach of the north passage are much larger than those in the lower reach. During neap tide, the calculations of Richardson number at different stations show that the channel in the upper reach is entirely mixed during ebb tide with $\text{Ri}<0.25$, while the lower reach water column is more stratified with $\text{Ri}>0.25$ mainly due to the saltwater-induced stratification. During spring tide, the Richardson number shows a similar distribution with stronger mixing in the upper reach of the channel and stronger stratification in the lower reach. These results are consistent with the findings of Song et al. [84]. Figures. 3.7 and 3.8 also compare the calculated eddy viscosities with and without sediment effects. Their differences are shown in the figures as well. In general, in the absence of sediment, eddy viscosities show higher values at all stations during both neap and spring tides. For example, the averaged eddy viscosities (AEVs) without sediment effects during neap tide at S3, S4 and S8 are $0.0027 \text{ m}^2\text{s}^{-1}$, $0.0022 \text{ m}^2\text{s}^{-1}$ and $0.00094 \text{ m}^2\text{s}^{-1}$, while they are $0.0019 \text{ m}^2\text{s}^{-1}$, $0.0016 \text{ m}^2\text{s}^{-1}$ and $0.00084 \text{ m}^2\text{s}^{-1}$ with sediment effects. The suspended sediment that induced stratification may reduce the eddy viscosity by 10~30%. During spring tide, AEVs for S3, S4 and S8 without sediment are $0.00527 \text{ m}^2\text{s}^{-1}$, $0.00634 \text{ m}^2\text{s}^{-1}$ and $0.00322 \text{ m}^2\text{s}^{-1}$ compared to $0.0038 \text{ m}^2\text{s}^{-1}$, $0.00518 \text{ m}^2\text{s}^{-1}$ and $0.00253 \text{ m}^2\text{s}^{-1}$ with sediment effects. The changes of the eddy viscosity by suspended sediments are 27.9%, 18.3% and 21.4%, respectively. Due to higher SSC, sediment effects on turbulent mixing is even more significant during spring. These results confirm that suspended sediments play a significant role in damping the turbulence and reducing mixing in the water column.
FIG. 3.7: Time series of eddy viscosities (m$^2$/s) (A) with and (B) without sediment effects and (C) eddy viscosity anomaly on August 12, 2012 (Neap tide) at (a) S3, (b) S4, (c) S6, (d) S8 and (e) S9.
FIG. 3.8: Time series of eddy viscosities ($m^2/s$) (A) with and (B) without sediment effects and (C) eddy viscosity anomaly on August 17, 2012 (Spring tide) at (a) S3, (b) S4, (c) S6, (d) S8 and (e) S9.

3.4.2 Bed shear stress and sediment sources

Figure 3.9 shows the along-channel tide-averaged SSCs during neap and spring tides. Clearly, the highest averaged SSC can be found in the middle reach (S3~S6) of the north
passage. During neap (Fig. 3.9a), the highest averaged SSC is located at S4, where the averaged SSC is more than 4 times larger than that at the entrance of the north passage (S1). During spring (Fig. 3.9b), the highest averaged SPC is found at S6, where the averaged SSC is about 15 times higher than that at S1. It can be concluded that the turbidity maximum in the north passage is located at the middle reach. The relationship between the formation of turbidity maximum and saltwater intrusion front has been discussed by many researchers [95, 87, 97]. Figure 3.10 shows the distributions of along-channel tide-averaged salinity during neap and spring tides and demonstrating a lag between seawater front and turbidity maximum, further proving the importance of saltwater intrusion front on the generation of turbidity maximum. However, it is still not clear where the suspended sediments in the middle reach come from. Generally, three suspended sediment sources can be identified: flush of the suspended sediments from the upstream as wash load, local resuspension from the bed and exchange of the sediments with the neighboring shoals. Clearly, the first mechanism fails to explain the high SSC in the middle reach because the SSC in the upper reach is quite low. To examine whether the suspended sediments in the middle reach of the north passage are from local resuspension, the bed shear stresses over the entire passage are calculated by a quadratic drag law

\[ \tau_b = \rho C_d u_b |u_b| \bigg|_{z=z_1} \]  \hspace{1cm} (3.6)

Where \( C_d \) is drag coefficient, \( z_1 \) is the height of the measurement location from the bed and
$u_b$ is current velocity at $z_1$. The drag coefficient is given by

$$C_d = \frac{u^2}{u^2|_{z=z_1}} = \frac{k^2}{[\log(z_1/z_0)]^2}$$

(3.7)

Where $z_0$ is roughness height. Based on numerical model calibration $[82]$, $z_0=0.2$ mm is used for Changjiang Estuary. Bed shear stresses are calculated for all stations and compared with the critical bed shear stress on both neap and spring tide conditions. The critical bed shear stress for erosion is chosen as $\tau_c = 0.2$ N/m$^2$ $[82]$, which is a typical value in Changjiang Estuary.

FIG. 3.9: The along-channel tide-averaged SSC (kg/m$^3$) during (a) neap and (b) spring tides. The highest SSC is located at the middle reach of the north passage (S3∼S6).
FIG. 3.10: The along-channel tide-averaged salinity (psu) during (a) neap and (b) spring tides. Turbidity Maximum is located at the middle reach of the north passage (S3~S6).

Fig. 3.11 shows the calculated bed shear stresses at S3, S4, S6, S8, S9 during neap tide. To facilitate the discussion, the time series of tidal currents as well as SSCs at these stations are also presented. Generally, the shear stress at ebb is larger than that at flood because of stronger ebb currents near the bed. The temporal variations of bed shear stress at S3 and S4 (Fig. 3.11a and 3.11b), which are located at the middle reach of the north passage, have a similar pattern. The bed shear stress at ebb is much greater than the critical shear stress for erosion $\tau_c$, resulting in the local resuspension of a large amount of sediments from the bed. The largest bed shear stress at S3 exceeds 3.5 N/$m^2$. The largest bed shear stress at S4 exceeds 2.5 N/$m^2$. During flood, bed shear stresses at these two stations are smaller than $\tau_c$. No sediments are expected to be suspended from the bed. However, very high suspended sediment concentrations are observed at both stations. It
can be inferred that the suspended sediments in the middle reach during flood are transported from a neighboring shoal, i.e. Jiuduan shoal located between the north and south passages (Fig. 3.1). This is confirmed by numerical simulations performed by Song et al. [98] and recent sediment flux measurements over the south jetty, which showed that the sediment transported into the north passage during flood is about $4.24 \times 10^9$ kg while the sediment transported out of the north passage during ebb is about $8.45 \times 10^7$ kg [99]. The net sediment transport over the south jetty is toward the north passage. At S6 (Fig. 3.11c), the shear stresses at both ebb and flood are larger than $\tau_c$, indicating that local resuspension is one of the dominant sediment sources. However, sediment exchange with the Jiuduan shoal can still be identified as a major source during flood as the SSC is higher while the bed shear stress is smaller compared to the ebb conditions. At other stations, the SSC distributions are consistent with bed shear stress variations. High SSCs appear at the times with larger bed shear stresses, indicating that the local resuspension plays a major role in suspended dynamics in the lower reach of passage.

The calculated bed shear stresses during spring tide are presented in Fig. 3.12. Due to stronger tidal currents, the bed shear stresses are much larger compared to neap tide condition. However, the general patterns of flood-ebb variability are quite similar with larger bed shear stresses at ebb and smaller bed shear stresses at flood. For example, at S4 and S6, the maximum bed shear stresses during flood are 4.18 and 2.97 N/m$^2$, respectively, while they are 7.13 and 13.26 N/m$^2$ during ebb. Nevertheless, the suspended sediment concentrations are much higher during flood at these two stations. Similar to the findings for the neap tide condition, it is because the suspended sediments in the middle reach of the passage during flood are significantly affected by the Jiuduan shoal. In the lower reach
of the passage (S8 and S9), the distributions of SSC are consistent with bed shear stress variations, although there are phase lags between these two.

FIG. 3.11: Time series of (A) velocity (m/s), (B) logarithm of SSC (kg/m³) and (C) bed shear stress (Pa) during neap tide at (a) S3, (b) S4, (c) S6, (d) S8 and (e) S9. The dashed lines show the critical shear stress for erosion. The shaded areas indicate the time when the bed shear stress is small while the SSC is high.
FIG. 3.12: Time series of (A) velocity (m/s), (B) logarithm of SSC (kg/m³) and (C) bed shear stress (Pa) during spring tide at (a) S3, (b) S4, (c) S6, (d) S8 and (e) S9. The dashed lines show the critical shear stress for erosion. The shaded areas indicate the time when the bed shear stress is small while the SSC is high.
3.5 SUMMARY

This research aimed to understand suspended sediment dynamics in the north passage of the Changjiang Estuary, particularly focusing on the net suspended sediment flux, sediment-induced stratification as well as sediment sources in the middle reach of the passage. Field measurements on tidal flow and SSC in summertime were collected and investigated.
CHAPTER 4

CONCLUSIONS AND FUTURE WORKS

In the second chapter of this dissertation the long term trends of extreme waves inside the Chesapeake Bay was investigated by means of extreme value analysis. The third-generation SWAN wave model was employed to obtain 3-hourly significant wave heights in the bay using a computational grid that covers the entire bay. The main findings of this study are listed as follows.

1. EOF analysis performed on daily-averaged SWHs shows seasonal variability of wave heights in the Chesapeake Bay with larger wave heights in winter season. It also reveals that the lower bay experiences more significant variations in wave height. Extreme storm events such as hurricanes and tropical storms can be detected from the first mode of PC.

2. Regression analysis on SWHs at Stingray Point suggests that there is a steady increase of extreme wave heights in the Chesapeake Bay. The continuous increase of extreme waves is further verified by empirical cumulative distribution function analysis for two separate periods: 1979-1997 and 1998-2015, in which a 9% increase in extreme wave height is observed in 99.5 percentile. These findings are confirmed by obtaining 99.5 percentile for the whole bay. Results suggest that except lower bay, where there is a maximum of 0.27m decrease in wave height, the rest of the bay receives an average wave height increase of 0.1 m.

3. The GEV and POT analyses performed on annual and monthly maxima and
independent extreme waves with threshold of 1.0 m and time span of 3 days show that return levels with 100-year return period evaluated from GEV for annual maxima data and GP model are higher than those from monthly maxima data by 10%. Therefore, annual maxima and POT approaches provide a more conservative estimate of design wave height for design purposes.

4. The effects of time span and threshold on design wave height are examined by tests on different time spans (3, 4, 5 and 6 days) and various thresholds (0.8, 0.9, 1, 1.1 and 1.2 m). It is found that increasing time span leads to larger design wave height, and higher threshold results in higher design wave height. Moreover, sensitivity analysis on data duration shows that a 28-year dataset can provide an acceptable estimate of design wave height in the bay.

5. The performance of GEV and GP is evaluated in terms of fitting the data against various distribution functions including Weibull, Gumbel, Gamma, Log-normal distribution functions using AIC/BIC test and Q-Q plots. Results indicate that Gamma and GEV provide the best fit for annual and monthly data, while GP gives the best fit when POT analysis is conducted.

While this research has provided useful information regarding wave characteristics inside the bay, several opportunities for extending the scope of this research remain to discuss in future as follows

1. In order to capture the surface gravity waves and swell a combination of nested computational grids can be used. Expanding the computational grids can help more accurately estimate the wave heights in and outside the bay. As a result, 50 or 100
year DWHs can also be evaluated for outside of the bay where coastal structures have more important role in protecting the shoreline. Besides, a sensitivity analysis can be performed on grid sizes to evaluate the accuracy of SWAN.

2. Although the variation of extreme waves are shown to be small inside the bay and extreme value analysis can be done using stationary extreme value theory, by expanding the computational grid and considering swells, non-stationary analysis can be performed and compared with stationary analysis to evaluate DWHs estimated using the stationary method and investigate the differences and potential impacts on coastal structures.

In the third chapter of this research data analysis was performed on field measurements including water level variations, tidal currents and SSCs at 9 stations in the north passage of the estuary during both neap and spring tide, to study sediment transport patterns in the summer time, to find out the likely sources of suspended sediment in the navigational channel, and to discuss the effects of suspended sediments on enhanced stratification of the water column in the DNC, which would affect net sediment flux and sediment deposition in the channel. This research provides useful information regarding impacts of sediments on stratification and turbulence mixing and also possible sources of suspended sediment in the Changjiang Estuary. The main findings of this study are listed as follows.

1. In the lower reach of the passage, two-layer tide-averaged circulation as well as sediment transport pattern are observed at both spring and neap with net sediment outflux in the upper water column and net sediment influx in the lower water
column. In the upper and middle reaches of the north passage, the role of advective flux in total sediment transport is much higher compared to the tidal flux during both neap and spring. Advective flux is responsible for about 70∼100% of total sediment transport. While in lower reach this amount reduces to 30∼60%.

2. Suspended sediment can greatly enhance the stratification in the water column. The sediment-induced stratification may reduce the eddy viscosity by 10∼30%. Due to high SSC during spring tide, the sediment effects on turbulent mixing are more significant.

3. The highest tide- and depth-averaged SSC is located in the middle reach of the north passage, where the averaged SSC is usually 4∼15 times higher than that in the upper reach. In the middle reach, the bed shear stress is larger at ebb because of the stronger ebb currents. However, the SSC is higher at flood. It can be inferred that suspended sediments in the middle reach during flood are transported from a neighboring shoal, i.e. the Jiuduan shoal, which plays an important role in the sediment dynamics in the north passage.

The following suggestions can be performed to enrich the quality of this study.

1. To investigate the seasonal variations of SSCs and hydrodynamic responses of the estuary to construction of the DNC, field data measurements can be performed during a different time of a year including dry and wet seasons at different locations in the estuary. The field measurements can help understand the role of river discharge, estuarine turbidity maximum, and their impacts on sediment deposition in the DNC.
2. Apart from field data analysis, a numerical study can be performed to study circulation and mixing in the estuary. The numerical study along with field observations can also help understand the mechanisms of sediment transport in Changjiang Estuary considering impacts of tide, waves, and river flows.
BIBLIOGRAPHY


[49] J. Allan and P. Komar, “Are ocean wave heights increasing in the eastern north pacific?,”

[50] J. C. Allan and P. D. Komar, “Climate controls on us west coast erosion processes,”


[70] A. Luceño, M. Menéndez, and F. J. Méndez, “The effect of temporal dependence on the estimation of the frequency of extreme ocean climate events,” in *Proceedings of the*


VITA

Arash Niroomandi
Department of Civil & Environmental Engineering
Old Dominion University
Norfolk, VA 23529

Arash Niroomandi was born in Shiraz, Iran, on September, 1983. After finishing his B.Sc. in Civil Engineering from Azad University in Shiraz, Iran, He received his M.Sc. in Water Resources Engineering from Sharif University of Technology in December 2009.