A Numerical Modeling Study of Storm Surge and Inundation in the Chesapeake Bay during the November 2009 Mid-Atlantic Nor’easter

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APPROVAL SHEET

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ABSTRACT

In this study, a prototype for the Chesapeake Bay inundation prediction system (CIPS) was developed using the parallel MPI version of the ELCIRC hydrodynamic model to examine the barotropic response of the Chesapeake Bay to the November 2009 Mid-Atlantic Nor’easter. A Nor’easter is a type of large-scale storm that mostly occurs in the winter along the East Coast of the United States. Because of its longer duration and larger spatial scale compared to those of a tropical cyclone (or hurricane), the nor’easter can cause severe floods to the coastal areas through cumulative effects during several tidal cycles over a prolonged period of time.

Forecast winds yielded from various atmospheric models were used as external forcings to drive the storm surge hydrodynamic model over a large domain, and the ensemble average of model results was calculated. Based on the comparison between the ELCIRC model results and NOAA tide/water level records compared at a number of stations in the Chesapeake Bay, the overall RMS error is 10 cm, which represents less than 5% of error normalized by the maximum water level during that period. It was also found that the surface wind drag coefficient was affected by the fetch-limited condition in the Upper Chesapeake Bay. By implementing the revised empirical surface drag coefficient over that area, the water level prediction in the Upper Bay was notably improved. The performance of the storm tide prediction was found to be highly dependent on the quality of predicted winds. The ensemble forecast approach was proved to be effective in reducing uncertainty and improving the overall predictive skill of the ELCIRC model.

A high-resolution small domain grid, which incorporates detailed LiDAR topographic data over the Greater Hampton Roads area, was also employed in ELCIRC for inundation simulation during the November 2009 Nor’easter. The predicted coastal inundation agreed very well with flooding records recorded by the USGS water level sensors. The CIPS’ successful experience suggested that an accurate inundation prediction demands (1) high-resolution wind and pressure fields as model inputs, (2) a proper portrayal of topography and bathymetry in the model grid, and (3) a reliable wetting-and-drying numerical scheme in the hydrodynamic model. Extra effort has been made to investigate the barotropic response of the Bay to remote and local winds during the November 2009 Nor’easter. It was found that the remote wind plays a dominant role in controlling water exchange between the continental shelf and the Chesapeake Bay through Ekman transport, while the local wind is responsible for short-term water level fluctuations inside the Bay, especially in the Upper Chesapeake Bay area.
A Numerical Modeling Study of Storm Surge and Inundation in the Chesapeake Bay during the November 2009 Mid-Atlantic Nor’easter
Chapter 1. Introduction

1.1 Background
1.1.1 Nor’easter

A Nor’easter, also referred to as an extratropical cyclone, or mid-latitude storm, is a type of macro-scale storm that moves along the East Coast of the United States and the Atlantic Canada, whose center of rotation is just off the East Coast and whose leading winds rotate onto land from the northeast. Nor’easters differ from tropical cyclones in that nor’easters are cold-core low-pressure systems that form in the middle latitudes and thrive on cold air, while tropical cyclones are warm-core low-pressure systems developed in the tropics.

Nor’easters may occur at any time of the year, but are mostly known for their formations in the winter season. These storms usually develop between Georgia and New Jersey within 100 miles of the coastline, and are drawn across to the northeast by the jet stream. They usually strengthen while moving to the north, and reach their peak intensities while off the Canadian Coast, with the strength sometimes equaling that of a strong hurricane. During a typical nor’easter, the temperature usually falls significantly, indicating the presence of cold air. High wind gusts and heavy precipitation are also associated with a nor’easter, which can cause severe rough seas, coastal flooding, and coastline erosions. A nor’easter can be extremely devastating and damaging during winter when frozen precipitation, such as heavy snow, is involved.

Though the occurrence of a nor’easter can be forecast with certain accuracy, predicting their impact on the coastal areas is more complex and challenging. Davis and Dolan (1993) created a Nor’easter intensity scale (see Appendix A) to classify those winter storms into 5 categories: 1 (Weak), 2 (Moderate), 3 (Significant), 4 (Severe), and 5 (Extreme), but it deals primarily with beach and coastal deterioration. Zielinski (2002) developed a new Nor’easter intensity scale from a climatologist point of view, which gives us more insight into the storms themselves. Basically, this new classification scheme allows forecasters and meteorologists to summarize a winter storm...
based on its intensity and duration. For example, a storm’s category might be 3.4, reflecting its intensity with the first digit 3 and duration with the second digit 4. The potential impact of the storm can then be passed to public service officials to help them with evacuation plans or decision-makings. However, until now, no official classification of the November 2009 Mid-Atlantic Nor’easter was published.

The November 2009 Mid-Atlantic Nor’easter (also referred to as “Nor’Ida”) was a powerful storm that caused widespread damage along the East Coast of the United States. This storm formed in relation to Hurricane Ida’s mid-level circulation across Georgia on November 10, and lasted over 7 successive days while moving northeast across North Carolina, Virginia, Delaware, New Jersey, and Long Island. Luckily, temperatures did not drop dramatically to cause a significant snowstorm to the coastal areas, a condition for which many nor’easters are notorious.

According to the surface weather analysis conducted by the Hydrometeorological Prediction Center (HPC) under the National Centers for Environmental Prediction (NCEP), by November 12, the system already had attained a minimum pressure of 992 mbar along the Eastern Shore of North Carolina. The position of the low created a tighter pressure gradient, resulting in stronger northeasterly winds over the Chesapeake Bay. On November 13, several NOAA stations in the southern Chesapeake Bay measured maximum winds. Notably, stations at Chesapeake Bay Bridge Tunnel and Yorktown measured wind speeds of 52 knots (26.6 m/s) and 42 knots (21.4 m/s), respectively, with maximum water levels being recorded a few hours later. The system began to weaken while slowly progressing along the Mid-Atlantic region of the Eastern United States, but still brought strong, steady northeasterly winds combined with heavy rainfalls to the Bay. It persisted through November 17, by which time it had moved over Atlantic Canada. Overall, the Lower Chesapeake Bay was affected the most by the storm, with the Upper Chesapeake Bay and parts of the Philadelphia area experiencing milder effects.

1.1.2 Coastal inundation during November 2009 Mid-Atlantic Nor’easter

The November 2009 Mid-Atlantic Nor’easter caused dramatic storm surge and inundation to the Chesapeake Bay coastal areas by bringing persistent onshore flows into the Bay. The NOAA
National Ocean Services (NOS) Center for Operational Oceanographic Products and Services (CO-OPS) recorded the Nor’easter event via a network of water level and current meter stations. CO-OPS meteorological data are also available in major ports and harbors, providing recorded winds (speed, direction and gust) and barometric pressure during the storm. Observed water levels in the Chesapeake Bay suggested that, at Money Point, Sewells Point, CBBT, and Kiptopeke, storm surge during the November 2009 Nor’easter exceeded record levels set by Hurricane Isabel in 2003, but the storm tide came very close. These illustrated the accumulative effect of sustained wind blowing on the set-up of coastal water levels.

In order to get verification data for coastal inundation during the November 2009 Nor’easter, the United States Geological Survey (USGS) rapidly deployed a water level and barometric pressure sensor network over the Greater Hampton Roads area to record the magnitude, extent, and timing of inland surge and coastal flooding. The deployed sensors continuously measured changes in pressure, and the data were corrected for salinity and barometric pressure to calculate the heights of water above the sensors. Then, water elevation at each sensor was determined in reference to a known vertical datum, in this case, the North American Vertical Datum of 1988 (NAVD 88). The hydrographs measured by the sensors can provide verification for numerical models which, in turn, can reveal the principle flow paths, as well as the intrusion and retreat of stream water. This special data collection for the November 2009 Mid-Atlantic Nor’easter was used to evaluate the predictive skill of the ELCIRC model on inundation predictions in Chapter 4.

1.2 Literature review

The Chesapeake Bay, one of the largest estuarine systems with heavily populated coastal regions along the US East Coast, is vulnerable to severe storm surge and inundation. Extreme weather events, such as hurricanes, are known to cause devastating damage to the coastal community. Recently, the nor'easter, which can deliver powerful storm surge to the Chesapeake Bay, has also drawn close attention. Nor'easters differ from tropical cyclones in that they are extra-tropical systems with a center of rotation frequently situated off the East Coast of North America and whose leading winds rotate onto land from the northeast. Their spatial scale coverages are on the order of 1000-1500 km and their durations range from 2-5 days. A northeaster can be especially
devastating to people’s lives and coastal properties during the winter season by bringing cold air from Arctic air masses, excessive precipitation, high winds, large waves, and prolonged storm surge. As a result, an efficient, real-time, event-triggered inundation prediction system is needed to assist coastal emergency managers and policy makers with decision-making and evacuation planning.

During the past several decades, many storm surge studies have been conducted in the Chesapeake Bay. Harris (1956) first introduced systematic studies into storm surges on the East Coast of the United States. In his 1963 paper on ‘characteristics of the hurricane storm surge’, five distinct processes were summarized as the key factors in controlling sea water level changes in the coastal area: (1) the pressure field effect, (2) the direct wind effect, (3) the effect of the Earth's rotation, (4) the effect of waves, and (5) the rainfall effect. Later, based on statistical analysis of historical events, Pore (1965) introduced two more factors that are important for the coastal surge in the Chesapeake Bay: (1) tidal elevation at the entrance of the Chesapeake Bay, and (2) modifying effects by the coastline and bathymetry within the Bay. Based on time series analysis, Wang (1979a,b) demonstrated that water level in the Bay responded to the local and remote wind forcings differently. The coastal ocean can influence the Bay water through alongshore Ekman transport. Chuang and Boicourt (1989) indicated that resonant seiche motion could occur inside the Chesapeake Bay during a northeaster wind event.

Since the early 1970s, storm surge studies using numerical models have become more popular and continue to improve by the infusion of new science knowledge and computational technology. Jelesnianski (1972) developed the first prototype of a storm surge model, SPLASH (the Special Program to List Amplitude of Surges from Hurricanes). After that, the SLOSH model (Sea, Lake, and Overland Surges from Hurricanes) was established and widely used by NOAA for coastal flooding studies in the Gulf Coast and Eastern Seaboard of the United States (Jelesnianski, 1974; Jelesnianski et al., 1992). Despite its popularity, the simplified numerical scheme and inability to resolve complex bathymetry and coastline boundaries using a structured grid have constrained the model’s capability for further improvement. The ADCIRC model (the ADvanced CIRCulation model) is the second-generation storm surge model (Luettich et al., 1991), which utilizes the generalized wave continuity equation (GWCE) to avoid the spurious oscillations associated with a primitive Galerkin finite element numerical scheme. It uses an
unstructured finite-element mesh to represent the domain and is optimal for adding complex coastal features in varying size when needed.

In recent years, due to the potential increase in the strength and frequency of storms related to global warming and sea level rise, there is renewed interest in calling for even more efficient, robust, and reliable storm surge and inundation forecast system for the US East Coast and Gulf Coast. (Valle-Levinson et al., 2002; Wang et al., 2005; Bernier and Thompson, 2006; Kohut et al., 2006; Li et al., 2006; Weisberg and Zheng, 2006; Shen et al., 2006a; 2006b; 2008). According to NOAA’s National Ocean Service, numerical models that are currently under development in the Coastal Ocean Modeling Framework include: ADCIRC (The ADvanced CIRCulation Model), ECOM (Estuarine, Coastal and Ocean Model), EFDC (Environmental Fluid Dynamics Code), ELCIRC (Eulerian-Lagrangian CIRCulation Model), FVCOM (Finite Volume Community Ocean Model), POM (Princeton Ocean Model), SELFE (Semi-implicit Eulerian-Lagrangian Finite Element Model), QUODDY (3D Finite Element Circulation Model), and ROMS (Regional Ocean Model System).

In this study, one of the new breeds of unstructured grid models, ELCIRC, was employed. The ELCIRC model encompasses the following salient features:

1) It uses an unstructured grid to resolve complex bathymetry and irregular coastlines.
2) It includes an efficient solver, which allows it to be less restricted by the CFL condition.
3) It allows a robust wetting-and-drying numerical scheme for inundation simulation.

Given the above features of the model, plus the boost of the parallel computing technique, it is promising to further establish it as a fast, robust, and reliable Chesapeake Bay Inundation Prediction System (CIPS) for forecast purposes.

1.3 Objectives and outline

The objective of this study is to build an efficient operational inundation forecast system for the Chesapeake Bay. Various forecast winds will be used as external forcings to drive the ELCIRC hydrodynamic model for storm surge and inundation simulations during the November 2009 Mid-Atlantic Nor’easter. In addition, sensitivity tests will be conducted to investigate the remote and
local wind effects, as well as the influence of continental shelf dynamics on water level fluctuations inside the Bay during this storm.

In order to fulfill the objective of developing a real-time storm surge and inundation forecast system for the Chesapeake Bay, several issues need to be addressed.
1) Both the storm surge in a large domain and the on-land inundation must be considered.
2) The implementation of the real-time forecast needs to be made operational.
3) The uncertainty introduced by different weather forecasts should be accounted for.

The following strategy and approach was adopted to deal with the issues mentioned above.
1) An approach of coupling a large domain grid with a high-resolution small domain grid was adopted for both storm surge and inundation simulation purposes.
2) A parallel MPI version of the ELCIRC hydrodynamic model was employed to improve the efficiency of storm surge forecasts.
3) To account for the uncertainty introduced by different weather forecasts, ensemble forecasts were conducted to improve the overall predictive skill of the ELCIRC model.

The specific tasks of this study are:
1) To prepare two versions of the model grid for both storm surge and inundation prediction purposes: the large domain grid covering the Atlantic West Coast from Nova Scotia to Florida, and the high-resolution small grid with high-resolution LiDAR data in the land portion of the Greater Hampton Roads area.
2) To set up the numerical modeling forecast system using the parallel MPI version of the ELCIRC, and calibrate the system using tidal boundary conditions.
3) To evaluate the accuracy of various forecast winds by comparing to meteorological records at NOAA tidal gauge stations.
4) To conduct storm surge and inundation simulations using an ensemble forecast approach, and to evaluate the model’s predictive skill by calculating a series of statistical measures.
5) To assess the model’s ability on inundation prediction by comparing to coastal flooding records recorded by USGS water-level sensors spanning the Greater Hampton Roads area.
6) To conduct sensitivity tests on remote and local wind effects, as well as the influence of continental shelf dynamics on water level fluctuations inside the Bay, to further investigate the
mechanism of the Bay’s response to the November 2009 Mid-Atlantic Nor’easter.

The ultimate goal of his study is to:
1) Develop an accurate, efficient, and event-triggered modeling system for coastal storm surge and inundation predictions.
2) Use the November 2009 Mid-Atlantic Nor’easter, which generated the 3rd largest storm surge in the Chesapeake Bay since 1933, as a case study to examine the barotropic response of the Bay to the storm.

The outline of the thesis is as follows:

In Chapter 2, a general introduction of the global and regional atmospheric models is given at the beginning. Then, the importance of ensemble weather forecast is addressed, following the proposal of conducting an ensemble ocean forecast to reduce uncertainty. Later, a detailed description of the ELCIRC hydrodynamic model is given, including its governing equations, treatment of bottom and surface boundary conditions, parameterization of turbulent vertical mixing, wetting and drying scheme, Coriolis force and tidal potential.

Chapter 3 describes the model configuration in this study, including the coupling of the large domain with the high-resolution small domain, the incorporation of LIDAR data in the small domain grid for inundation simulation purposes, as well as the adoption of the parallel computing technique in the ELCIRC model.

A series of storm surge and inundation simulations are conducted in Chapter 4, and results are presented and analyzed here. Before that, the ELCIRC model is calibrated using a harmonic tide at its open boundary. Then, forecast winds were evaluated based on statistical measures. To evoke the ensemble forecast approach, multiple forecasts are conducted using various forecast winds as external forcings. Model results are compared to NOAA water level observations for storm surge evaluation, and compared to USGS flooding records for inundation assessment. More effort is made to investigate the influence of fetch-limited surface drag coefficient on water level fluctuations in the Upper Bay area.
As a further study, sensitivity tests are conducted in Chapter 5 to investigate the barotropic response of the Bay to the November 2009 Mid-Atlantic Nor’easter. Specifically, three subjects are raised and studied: 1) the feasibility of conducting real time ensemble forecast using the parallel MPI version of the ELCIRC model, 2) the effects of the remote and local winds on regional water level fluctuations inside the Bay, and 3) the influence of continental shelf dynamics on storm surge inside the Bay.

Chapter 6 summarizes the work being done in this study, and gives a final conclusion and discussion.
Chapter 2. Description of atmospheric models and ELCIRC hydrodynamic model

2.1 Description of atmospheric models

2.1.1 Global and regional atmospheric models

An atmospheric model is a mathematical model constructed around the full set of primitive dynamical equations that govern atmospheric motions. It can predict microscale phenomena such as tornadoes, sub-microscale turbulent flow over buildings, as well as synoptic and global flows by supplementing the primitive equations with parameterizations for solar radiation, moist processes, heat exchange, soil, vegetation, surface water, the effects of terrain, and convection. The primitive equations in the atmospheric models are nonlinear and thus are impossible to solve exactly through analytical methods. Therefore, numerical methods are applied in the model to obtain approximate solutions.

Numerical weather prediction uses atmospheric models to predict the weather based on the current weather conditions. Although first attempted in 1920s, it was not until the advent of computer simulation in the 1950s that weather predictions produced realistic and usable results. Manipulating the vast datasets and performing the complex calculations require some of the most powerful supercomputers in the world. Even with the increasing power of supercomputers, the forecast skill of numerical weather models only extends to a few days into the future. Factors affecting the accuracy of numerical predictions include the density and quality of observations used as input to the forecasts, along with deficiencies in the numerical models themselves. Due to the chaotic nature of the partial differential equations used to simulate the atmosphere, it is impossible to solve these equations exactly, and small errors grow with time. Since the 1990s, ensemble forecasts have been used to help quantify the large amount of inherent uncertainty remaining in numerical predictions, and to generate useful results farther into the future than otherwise possible.
To start a forecast, a model needs to be initialized using the observational data. A variety of methods are used to gather observational data for use in numerical models, such as radiosondes, weather satellites, aircraft and ships, etc. According to Richardson’s early attempt to forecast weather numerically, observations cannot be used directly to initialize a numerical forecast. The irregularly spaced observations need to be processed to obtain a suitable set of data for model initialization, which is referred to as data assimilation. Then, the future state of the atmosphere is computed at each time step by solving the primitive equations numerically, and time stepping is repeated until the solution reaches the desired forecast time. The output produced by a model solution is known as a prognostic chart.

Based on the horizontal domain, an atmospheric model is either global, covering the entire Earth, or regional, covering only part of the Earth. Each type has its own strength and merits, thus being used for different prediction purposes. Currently, a number of global and regional atmospheric models are applied in different countries worldwide to produce both short-term weather forecasts and long-term climate predictions.

The Global Forecast System (GFS) is a global atmospheric model run by NOAA for weather prediction purposes. Output from this model is available in the public domain over the Internet, and is the basis for many regional models. This model runs four times a day and produces forecasts up to 16 days in advance, with decreasing spatial and temporal resolutions over time. There are other well-known global atmospheric models being applied in different countries like Canada and the United Kingdom, which will not be discussed in this study. Currently, the GFS deployed by the NOAA National Centers for Environmental Prediction (NCEP) has a horizontal resolution of 32 km, which is inadequate to resolve the detailed wind fields over the Chesapeake Bay and its tributaries. Therefore, various regional atmospheric models are being applied for more desirable weather predictions.

Regional models are also known as limited-area models (LAMs). They use a compatible global model to provide boundary conditions at the edge of the regional domain, and employ much finer grid spacing in order to resolve smaller-scale meteorological phenomena. Time steps for regional models are usually between one and four minutes, chosen to maintain numerical stability while considering computational demands. The advantage of using regional atmospheric models is that
they allow for significant improvements in predicting tropical cyclone track and detailed wind fields over land.

The WRF (Weather Research and Forecasting) model is a mesoscale numerical weather prediction system designed to serve both operational forecasting and atmospheric research needs. The WRF model features multiple dynamical cores, a 3-dimensional variational (3DVAR) data assimilation system, and a software architecture allowing for computational parallelism and system extensibility. WRF is suitable for a broad spectrum of applications across spatial scales ranging from meters to thousands of kilometers, and can be tailored for a workstation for a specified local modeling domain. There are two distinct varieties of this model. The ARW (Advanced Research WRF) features very high resolution and is designed to meet advanced research purposes. The NMM (Nonhydrostatic Mesoscale Model), on the other hand, is designed for forecasting operations. The National Weather Service (NWS) office at Wakefield, Virginia (AKQ, http://www.erh.noaa.gov/er/akq/) currently runs the WRF-NMM with 4-km resolution grid spacing in the Chesapeake Bay. This model is able to produce detailed banding structures in tropical systems and wind field changes at fine scales.

The North American Mesoscale model (NAM) refers to a numerical weather prediction model that covers the North American domain and is run by NCEP for short-term weather forecasting. Beginning in May 2006, the Weather Research and Forecasting Non-hydrostatic Mesoscale Model (WRF-NMM) model is run as the NAM for operational needs. The model is run four times a day (00:00, 06:00, 12:00, and 18:00 Greenwich Mean Time (GMT)) out to 84 hours, and has a 12-km horizontal resolution and 1-hour temporal resolution. It provides finer details of the wind field and the pressure field than does the GFS global model.

The RAMS (Regional Atmospheric Modeling System) is a mesoscale atmospheric computer model first developed at Colorado State University, and being updated continuously since it first became operational. With multiple salient features built in, RAMS boasts a unique ability to be specifically and precisely tailored for a particular meteorological regime. The WeatherFlow (http://www.weatherflow.com/) runs an operational version of the RAMS, offering high-resolution forecasts in domains covering most of the coastal United States.
2.1.2 Ensemble forecast to reduce uncertainty

Currently, forecasts made by atmospheric models only extend to a few days into the future. Factors affecting the accuracy of numerical predictions include the density and quality of observations used to initialize the forecasts, along with the deficiencies in the models themselves, such as numerical schemes they apply to solve the equations. In an effort to account for the large amount of inherent uncertainty remaining in atmospheric predictions, ensemble weather forecasts have been used since the 1990s to help gauge the confidence in the forecast, and to generate representative results from all participating members. Ideally, the verified weather pattern should fall within ensemble spreads, and the amount of spread should be related to the probability of certain weather events occurring. Ensemble data can be viewed on spaghetti plots, ensemble means, or Postage Stamps. At present, ensemble predictions are commonly made at most of the major operational weather prediction facilities worldwide.

A storm surge is an offshore rise of water associated with a low-pressure weather system, typically tropical cyclones or extratropical cyclones. Surges are primarily caused by high winds pushing on the ocean surface. During a storm, the water body responds to the atmospheric forcing, causing the water to pile up higher than ordinary sea level. Low pressure at the center of the weather system also affects the total water level through the inverse barometric effect. It is this combined effect of both high winds and low pressure that is mainly responsible for coastal flooding problems. Thus, accurate prediction of the ocean state during extreme weather events depend highly on the quality of predicted wind and pressure fields made by atmospheric models.

As uncertainties in hurricane model forecasts would affect storm surge predictions in a semi-enclosed bay (Zhong et al., 2010), multiple storm surge forecasts were conducted simultaneously using the ELCIRC model driven by various meteorological forcings, and the ensemble average was calculated as a representative of all individual results. Specifically, three sets of forecast winds, including the 12-km resolution NAM wind, the 4-km resolution WRF wind, and the 2-km resolution RAMS wind, were employed to drive the ELCIRC hydrodynamic model for storm surge and inundation predictions inside the Chesapeake during the November 2009 Mid-Atlantic Nor’easter. Ensemble results were obtained to examine the overall predictive skill of the ELCIRC model.
2.2 Description of ELCIRC hydrodynamic model

The ELCIRC is an unstructured-grid model designed for the effective simulation of 3D barotropic/baroclinic circulation across river-to-ocean scales, using an orthogonal, unstructured grid with mixed triangular and quadrilateral grids in the horizontal and z-coordinates in the vertical. It solves the shallow water equations using a finite-volume/finite-difference Eulerian-Lagrangian algorithm to address a wide range of physical processes and of atmospheric, ocean and river forcings. Although the numerical algorithm is low-order, it is volume conservative, stable, and computationally efficient. This model also incorporates a natural handling of wetting and drying of tidal flats, which allows it to simulate coastal inundation accurately. ELCIRC has been released as a community model and its open-source code can be found at http://www.ccalmr.ogi.edu/CORIE/modeling/elcirc/index.html.

2.2.1 Governing equations

The ELCIRC model solves for the free surface elevation, 3D water velocity, salinity, and temperature, using a set of 6 hydrostatic equations based on the Boussinesq approximation, which represent mass conservation (in both 3D and depth-integrated forms), momentum conservation, and conservation of salt and heat:

**Continuity Equation**

\[
\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} = 0 \quad \Rightarrow \quad \frac{\partial \eta}{\partial t} + \frac{\partial}{\partial x} \int_{H_{x-h}} \eta \, u \, dz + \frac{\partial}{\partial y} \int_{H_{x-h}} \eta \, v \, dz = 0
\]

**Momentum Equations**

\[
\frac{Du}{Dt} = f \nu \frac{\partial}{\partial x} \left\{ g(\eta - \alpha \psi) + \frac{P_u}{\rho_0} \right\} - \frac{g}{\rho_0} \int_{H} \frac{\partial p}{\partial x} dz + \frac{\partial}{\partial z} \left( K_m \frac{\partial u}{\partial z} \right) + F_{nx}
\]

\[
\frac{Dv}{Dt} = -f \nu \frac{\partial}{\partial y} \left\{ g(\eta - \alpha \psi) + \frac{P_u}{\rho_0} \right\} - \frac{g}{\rho_0} \int_{H} \frac{\partial p}{\partial y} dz + \frac{\partial}{\partial z} \left( K_m \frac{\partial u}{\partial z} \right) + F_{ny}
\]

\[
\frac{\partial p}{\partial z} = -\rho g
\]
Equation of State
\[ \rho = \rho(S, T) \]

Transport of Salt and Temperature
\[ \frac{DS}{Dt} = \frac{\partial}{\partial z} \left( K_{sv} \frac{\partial S}{\partial z} \right) + F_s \]
\[ \frac{DT}{Dt} = \frac{\partial}{\partial z} \left( K_{sv} \frac{\partial T}{\partial z} \right) + \frac{Q}{\rho_0 C_p} + F_h \]

where
- \((x, y)\) horizontal Cartesian coordinates, \((m)\)
- \((\phi, \lambda)\) latitude and longitude
- \(z\) vertical coordinate, positive upward, \((m)\)
- \(t\) time, \((s)\)
- \(H_r\) \(z\)-coordinate at reference level (geoid or mean sea level (MSL))
- \(\eta(x, y, t)\) free-surface elevation, \((m)\)
- \(h(x, y)\) bathymetric depth, \((m)\)
- \(\frac{1}{i} \mathbf{u}(x, t)\) water velocity at \(\mathbf{i} = (x, y, z)\), with Cartesian components \((u, v, w)\), \((ms^{-1})\)
- \(f\) Coriolis factor, \((s^{-1})\)
- \(g\) acceleration of gravity, \((ms^{-2})\)
- \(\psi(\phi, \lambda)\) tidal potential, \((m)\)
- \(\alpha\) effective Earth elasticity factor \((\approx 0.69)\)
- \(\rho(x, t)\) water density; by default, reference value \(\rho_0\) is set as 1025 \(kgm^{-3}\)
- \(P_a(x, y, t)\) atmospheric pressure at the free surface, \((Nm^{-2})\)
- \(S, T\) salinity and temperature of the water, (practical salinity units (psu), \(^oC\))
- \(K_{sv}\) vertical eddy viscosity, \((m^2s^{-1})\)
- \(K_{sv}, K_{sh}\) vertical eddy diffusivity, for salt and heat, \((m^2s^{-1})\)
- \(F_{mx}, F_{my}, F_s, F_h\) horizontal diffusion for momentum and transport equations
\[ Q(\phi, \lambda, z, t) \] rate of absorption of solar radiation \((Wm^{-2})\)

\[ C_p \] specific heat of water \((Jkg^{-1}K^{-1})\)

The differential system for the 6 primary variables \((\eta, u, v, w, T, S)\), is closed with the equation of state (water density as a function of salinity and temperature), the tidal potential and Coriolis factor, parameterization of vertical mixing, and appropriate initial and boundary conditions.

The ELCIRC storm surge model solves for the free surface elevation, and 3D water velocity for the barotropic mode under the hydrostatic condition.

### 2.2.2 Initial and Boundary conditions

**Initial condition**

The governing equations require, in general, the initial condition (for elevation, velocities, salinity and temperature) to start the model. Since only the barotropic mode of ELCIRC is enacted for storm tide simulation, the initial condition applied is the no motion condition and the model is “spun up” by the tidal elevation specified at the open boundary using a ramp up function. The ramp function being used is a hyperbolic tangent function and the duration is 1 to 2 days. For a large domain, the tidal potential forcing also needs to be turned on.

**Surface Boundary conditions**

At the sea surface, ELCIRC enforces the balance between the internal Reynolds stress and the applied shear stress, i.e.

\[ \rho_0 K_{mv} \left( \frac{\partial u}{\partial z} \cdot \frac{\partial v}{\partial z} \right) = (\tau_{wx}, \tau_{wy}) \text{ at } z = H_R + \eta \]

The surface wind stress over the ocean is a crucial forcing in the storm surge modeling. ELCIRC allows for two different approaches to the parameterization of spatially and temporally variable surface shear stresses. One approach consisting of the use of a bulk aerodynamic algorithm (Zeng et al., 1998) to account for ocean surface fluxes under various conditions of stability of the
atmosphere, is recommended, especially when ELCIRC is used in conjunction with (or more commonly forced by outputs from) an atmospheric model. Surface stresses can be evaluated as

\[
(\tau_{wx}, \tau_{wy}) = \rho_a C_{Da} \left| \vec{W} \right| (W_x, W_y)
\]

where \( \rho_a \) is the air density (kg/m\(^3\)), \( C_{Da} \) is the wind drag coefficient, \( \vec{W}(x,y,t) \) is the wind velocity at 10 m above the sea surface, with magnitude \( |\vec{W}| \) and components in east-west \( W_x \) and north-south \( W_y \) (m/s).

The drag coefficient \( C_{Da} \) is usually determined empirically by fitting observational data to a curve. In Large and Pond’s formula (1981), the equation concerning \( C_{Da} \) is in the form of a linear function.

\[
C_d = (a + b |\vec{W}|) \times 10^{-3}
\]

Although there is considerable discrepancy among the parameters \( a \) and \( b \) proposed by different authors, here \( a = 0.49 \) and \( b = 0.065 \). The lower limit of the formula, 4 m/s, is based on the work of Donelan et al. (2004), and the upper limit of the formula, 33 m/s, is based on the investigation of Powell et al. (2003). For moderately strong winds, this formula allows the amount of the momentum being transferred through the air-sea interface to increase with growing wind speed. \( C_{Da} \) remains constant outside the range.

\[
C_{Da} = 10^{-3} \times \left( 0.49 + 0.065 |\vec{W}| \right) \quad \text{if} \quad \left| \vec{W} \right| \leq 4 \text{m/s}
\]

\[
C_{Da} = 0.75 \times 10^{-3} \quad \text{if} \quad \left| \vec{W} \right| \leq 4 \text{m/s}
\]

\[
C_{Da} = 2.64 \times 10^{-3} \quad \text{if} \quad \left| \vec{W} \right| \geq 33 \text{m/s}
\]

**Bottom boundary conditions**

As is customary, this model enforces the balance between the internal Reynolds stress and the bottom frictional stress at the sea bottom.

\[
\rho_0 K_{mv} \left( \frac{\partial u}{\partial z} - \frac{\partial v}{\partial y} \right) = (\tau_{bx}, \tau_{by}) \quad \text{at} \quad z = H - h
\]
And the bottom stress is defined as:

\[
(\tau_x, \tau_y) = \rho_g C_{Db} \sqrt{u_b^2 + v_b^2} (u_b, v_b)
\]

where \(u_b, v_b\) are bottom velocities, and \(C_{Db}\) is bottom drag coefficient. In order to model bottom stress properly, an accurate parameterization of \(C_{Db}\) is required. Typically, \(C_{Db}\) varies in space and also temporal scales and, thus, site-specific calibration is often required. Instead of using a constant drag coefficient \(C_{Db}\) for the entire domain, a logarithmic law is often applied to calculate the spatial-varied \(C_{Db}\) by specifying the local bottom roughness (in meters) at each node. The latter requires a rather finer discretization of the bottom in the model grid to get good estimations of \(C_{Db}\). However, in the depth-averaged long wave model, \(C_{Db}\) is often obtained using Manning’s formula:

\[
C_{Db} = \frac{g n^2}{\Delta z^{1/3}} , \quad 0.001 < C_{Db} < 0.003
\]

where \(g\) is the gravity acceleration (\(m/s^2\)), \(n\) is the Manning coefficient, and \(\Delta z\), in this case, is the total depth of the water column.

The Manning coefficient \(n\) is an empirically derived coefficient, which depends on many factors including surface roughness and sinuosity. In natural streams, \(n\) varies greatly along its reach, and even varies in a given reach of channel with different stages of flow. Due to lack of field inspection, \(n\) is treated simply as a constant in this study, and is adjusted for the best simulation results during tidal calibration in Chapter 4.

Open boundary conditions
In the tidal simulation, it is adequate to use a Dirichlet boundary condition at the open boundary, for which the elevation is set to the specific known value as follows:

\[
\eta = \hat{\eta}
\]

For the large domain grid, values of the water elevation \(\hat{\eta}\) specified at the open boundary were calculated using 13 tidal constituents, which were obtained from the U.S. Army East Coast 2001
2.2.3 Parameterization of turbulent vertical mixing

Parameterization of turbulent vertical mixing is very important for a three-dimensional storm surge model to function properly under high wind forcing conditions. ELCIRC allows for multiple choices among many approaches of widely varying complexity that have been proposed in the literature. Currently, turbulence models that have been coded in ELCIRC include a zero-equation model (based on Pacanowski and Philander (1981)), the traditional 2.5 closure model of Mellor and Yamada (1982) as modified by Galperin et al. (1988), and the generic length scale (GLS) closure model proposed by Umlauf and Burchard (2003).

The two-and-a-half turbulence models have been tested in this study, but did not yield satisfactory results. One possibility is that the resolution of the vertical grid being employed is not high enough to yield accurate result. In fact, the ELCIRC model uses a z-coordinate in the vertical grid, which creates a staircase representation of the bottom and reduces the shallow water area from 3D to 2D. More layers need to be specified in order to let these 2.5 closure models perform properly. However, by doing so, computational demands will dramatically increase, thus jeopardizing the robustness of the model.

Therefore, rather than selecting a built-in turbulent scheme in ELCIRC, a semi-empirical formula combining current-dependent eddy viscosity with wind wave-dependent eddy viscosity (Davies et al., 1997), was coded and implemented in ELCIRC during this study. The formulation of wind wave-dependent eddy viscosity was based on Dobroklonsky (1947) and Ichiye (1967). The formulae are given as:

\[ K_z = K_0 + 0.0025 h |U| + 0.028 \frac{H^2}{T} e^{-2\pi \frac{z}{L}} \quad h \leq 200m \]

\[ K_z = K_0 + 0.0025 |U|^2 + 2.84 \times 10^{-5} \times \frac{H}{g} e^{-2\pi \frac{z}{L}} \quad h > 200m \]
where:
\( K_z \) eddy viscosity at vertical layer \( z \) \((m^2/s)\).
\( K_0 \) background eddy viscosity (set to 0.0005 \( m^2/s \)).
\( h \) water depth (m).
\( |U| \) vertically averaged velocity (m/s).
\( H \) significant wave height (m).
\( T \) average wave period (s).
\( z \) depth of the layer (m).
\( L \) wave length (m).
\( |W| \) wind magnitude (m/s).

The formulations of vertical viscosity are different in shallow water and deep ocean water. Near the coast or inside the Bay, where water depth is commonly less than 200 m, the eddy viscosity generated by current is \( 0.0025h|U| \), and the wave-generated eddy viscosity is \( 0.028\frac{H^2}{T}e^{-2\pi\frac{z}{L}} \). In the deep ocean, the current-generated eddy viscosity is over-estimated using \( 0.0025h|U| \) as \( h \) increases. Instead, \( 0.0025|U|^2 \) is used according to Davies et al. (1997). Also, the wave-generated eddy viscosity is calculated by \( 2.84 \times 10^{-5}\frac{|W|^3}{h}e^{-2\pi\frac{z}{L}} \).

Statistics of wave height for wave records follows a Rayleigh distribution in general. However, this may not be true for shallow-water waves, which are strongly modulated by bathymetric effects combined with the amplitude nonlinearities. Under certain circumstances, determinations of significant wave height \( H \), wave period \( T \) and wave length \( L \) inside the Chesapeake Bay during the storm are usually through empirical formulae. In general, \( H \) is calculated by
\[ H = 2.12 \times 10^{-2}|W|^2, \]
\( T \) is calculated by
\[ T = 0.81\frac{2\pi|W|}{g}, \]
and \( L \) is calculated by
\[ L = \frac{gT^2}{2\pi} \sqrt{\tanh\left(\frac{4\pi^2}{L}\frac{h}{T^2} \frac{g}{h}\right)}. \]
2.2.4 Wetting and drying scheme

A natural and robust handling of wetting and drying was retained in ELCIRC by applying formulations of Casulli and Cheng (1992) and Casulli and Zanolli (1998), which make accurate inundation simulation near the coast possible. Generally, this approach allows primarily careful bookkeeping of indices. After all unknowns have been found for time step n+1, the free-surface indices are updated with the newly computed elevations. Elements are dried if \( h + \eta < h_o \) (\( h_o \) is a small positive number used in the code in lieu of zero in order to avoid underflow). Otherwise, elements are wet. When only one vertical layer is specified, this method reduces to a semi-implicit scheme for solving the corresponding two-dimensional shallow water equations. The resulting two-dimensional or three-dimensional algorithm in ELCIRC has been shown to be efficient, accurate and mass conservative and is recognized to simulate flooding and drying in tidal flats and near-shore areas.

2.2.5 Coriolis force and tidal potential

The earth rotation is represented through the Coriolis acceleration in the momentum equations. In three-dimensional space the Coriolis acceleration is given by

\[
\text{Coriolis} = \begin{pmatrix}
2\Omega v \sin \Phi - 2\Omega \omega \cos \Phi \\
-2\Omega u \sin \Phi \\
2\Omega u \cos \Phi
\end{pmatrix}.
\]

When vertical velocity \( w \) is much smaller than the horizontal components \( u \) and \( v \), this expression is approximated by

\[
\text{Coriolis} = \begin{pmatrix}
f v \\
- f u \\
0
\end{pmatrix},
\]

where \( f(\Phi) = 2\Omega \sin \Phi \), and \( \Omega = 7.29 \times 10^{-5} \text{rads}^{-1} \) is the angular velocity of rotation of the earth. It is also assumed that the vertical Coriolis acceleration can be neglected with respect to gravity \( g \).
To minimize coordinate inconsistencies dealing with Cartesian coordinate in a large domain, the ELCIRC uses a \( \beta \)-plane approximation for \( f \):

\[
f = f_c + \beta_c (y - y_c),
\]

where subscript \( C \) denotes the mid-latitude of the domain and \( \beta \) is the local derivative of the Coriolis factor \( f \). When the horizontal domain is not too large (100km), the \( f \)-plane approximation is used instead of the \( \beta \)-plane approximation, where the Coriolis parameter \( f \) may be taken to be constant at its value at the center of the area (in this case, at latitude 37° N).

To simulate large-scale tide, the tidal potential is defined following Reid (1990):

\[
\hat{\psi}(\phi, \lambda, t) = \sum_{n,j} C_{jn} f_{jn}(t_0) L_j(\phi) \cos \left[ \frac{2\pi(t - t_0)}{T_{jn}} j\lambda + v_{jn}(t_0) \right],
\]

where

- \( C_{jn} \) constants characterizing the amplitude of tidal constituent \( n \) of species \( j \) (\( j = 0 \), declinational; \( j = 1 \), diurnal; \( j = 2 \), semi-diurnal), (m)
- \( t_0 \) reference time
- \( f_{jn}(t_0) \) nodal factors
- \( v_{jn}(t_0) \) astronomical arguments, (r)
- \( L_j(\phi) \) species-specific coefficients (\( L_0 = \sin^2 \phi; L_1 = \sin(2\phi); L_2 = \cos^2 \phi \))
- \( T_{jn} \) period of constituent \( n \) of species \( j \)
Chapter 3. Set up of Chesapeake Bay storm surge and inundation prediction system

3.1 Hydrodynamic Model Configuration

3.1.1 Horizontal grid and vertical grid

The ELCIRC model operates over an orthogonal, unstructured grid with mixed triangular and quadrilateral cells in the horizontal and un-stretched z-coordinates in the vertical. The combined horizontal and vertical discretizations that result over the entire 3D domain are divided into a series of prisms. The depths at each side are calculated from depths at nodes, and depths in each element are taken to be the maximum of depths at its sides. This results in a staircase representation of the bottom.

As discussed by Casulli and Zanolli (1998), orthogonality is a requirement for calculation of finite difference approximations of spatial gradients in unstructured grids. In practice, this requirement might be relaxed, but the accuracy of solutions suffers from deviations from orthogonality. While a second-order accuracy can be achieved with uniform structured or unstructured orthogonal grids, a first-order accuracy is attainable only with non-uniform orthogonal grids. Also, an additional source of errors is introduced due to the fact that the line connecting the two element centroids is not perpendicular to the common side for general non-orthogonal grids.

In this study, a fast and efficient grid generator processor, JANET (Java net generator), was used for generating, analyzing, and optimizing unstructured orthogonal grids for the ELCIRC model. This software has many useful grid generation modules, which include: 1) digital models to represent the basic design information; 2) different methods for grid generation that rely on the basic design information; 3) coupling techniques for sub-grids of different grid structure to setup complex unstructured models; 4) modules to analyze and optimize the model; and 5) a module to export to a model’s specific file format. These different modules enable the definition of sub
domains with varying grid structures. For example, quadrilateral grid cells are usually generated to represent narrow channels by discretizing the channel with a constant number of polygons per cross section and allowing asymmetric profiles for a better alignment of the polygons to the isobaths of the Digital Terrain Model. Also, fine triangular grid cells are often generated near the coast for better representation of the complex shorelines. Then, these sub-grids are coupled to an entire unstructured grid with the software’s sub grid module, which allows splitting, merging, and copying sub-grids. Later, various analysis functions allow a detailed assessment of the model. Last but not least, different optimization methods are employed to improve the grid for specific properties, such as orthogonality.

Recognizing that a small domain is inadequate for simulating storm surge accurately without considering offshore conditions (Li et al., 2006; Shen et al., 2008), an approach of coupling a large domain with a high-resolution small domain was adopted in this study. Two versions of model grids were generated using the processor JANET: a large domain grid covering the Atlantic West Coast from Nova Scotia to Florida with a relatively coarse resolution (Figure 3.1), and a high-resolution small domain grid covering the Chesapeake Bay, as well as the land portion of the Greater Hampton Roads area (Figure 3.2). While the large domain is used to account for offshore effects, the high-resolution small domain, which incorporates the LiDAR topographic data in the Greater Hampton Roads area, allows the ELCIRC model to simulate storm surge and inundation accurately. The open boundary for the small domain was specified by time series of water level data extracted from the large domain outputs.

In the vertical, the 3D domain is discretized into a series of layers based on unstretched z-coordinates. Each layer extends throughout the entire domain, and is numbered sequentially upwards. In this study, 30 layers were used in the vertical. The thickness of layers varied with water depth, typically with a coarse resolution in the deep ocean, and finer resolution near the surface. The choice of z-coordinates enables a natural treatment of wetting and drying, but creates a staircase representation of the bottom, which limits the representation of the bottom boundary layer.
Figure 3.1  The large domain grid covering the Atlantic West Coast from Nova Scotia to Florida
Figure 3.2   The high-resolution small domain grid covering the Chesapeake Bay as well as the land portion of the Greater Hampton Roads area
3.1.2 LiDAR data

Both the large domain grid and the high-resolution small domain grid are interpolated with high-resolution bathymetric data to represent realistic bathymetry in the Chesapeake Bay. In addition, the high-resolution small domain grid was incorporated with high-resolution topographic data from a LiDAR (Light Detection And Ranging) dataset covering the land portion of the Greater Hampton Roads area for the inundation simulation purpose. LiDAR is an optical remote sensing technology that measures the distance to, or other properties of, a target by illuminating the target with light, often using pulses from a laser. The distance of an object can be determined by measuring the time delay between the emission of a pulse and the detection of the reflected signal. Thus, a narrow laser beam can be used to map physical features of the land with very high resolution.

In this study, the original LiDAR data being used have a horizontal resolution of 1m-by-1m. As the resolution of the ELCIRC grid is only on the order of tens of meters, the LiDAR data were first re-mapped to a 10m-by-10m grid to reduce the amount of data being handled next. After the pre-processing, the smaller dataset were interpolated to the ELCIRC grid using a bilinear interpolation scheme. Minor modifications were done manually at the final stage for a better representation of trivial land features, such as narrow creeks in the inter-tidal zone. The combination of high-resolution bathymetry and topography in the model grid allows ELCIRC to generate more accurate storm surge and coastal inundation simulations.

3.2 Parallel computing with MPI

In order to take full advantage of the parallel computing technology nowadays and enhance model efficiency, a parallel MPI version of ELCIRC was employed in this study. The MPI (Message-Passing Interface) is a portable standard for programming parallel computers that allows data to be passed between processes in distributed memory environment. The parallel MPI implementation of ELCIRC was developed based on a parallel version using PATHS (Bjørndalen, 2003). In the parallel MPI version, MPI is used for communication.
The ELCIRC model was parallelized through domain decomposition using ParMETIS. ParMETIS is an MPI-based parallel library that implements a variety of algorithms for partitioning unstructured graphs, meshes, and for computing fill-reducing orderings of sparse matrices. The domain is first partitioned into non-overlapping sub-domains (in element sense). Then, each sub-domain is augmented with one layer of ghost elements where exchange of info will occur. The size of the ghost regions relative to the size of the region is essential for the scalability of this application, as a larger ghost region means more data need to be communicated during the implementation of the code.

A heterogeneous cluster computing system named SciClone at the College of William & Mary served as a powerful computing platform for us to conduct a series of simulations using the parallel code. SciClone is presently arranged as eight tightly coupled sub-clusters, which can be used individually or together. Specifically, a sub-cluster named Typhoon with 72 dual-processors, dual-core Dell SC1435 was used in this study. The scalability of the parallel code was tested in realistic cases using different numbers of processors each time, and the CPU time being consumed is listed in Table 3.1. It suggested that the computing efficiency could be greatly improved by using more processors simultaneously. However, further improvement could be limited by using more than 32 processors, as the size of the current model domain is not significantly large.

Table 3.1   Scalability test for the parallel MPI version of ELCIRC

<table>
<thead>
<tr>
<th>Processors</th>
<th>CPU time (min) for 1-day simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100.3</td>
</tr>
<tr>
<td>2</td>
<td>64.9</td>
</tr>
<tr>
<td>4</td>
<td>17.7</td>
</tr>
<tr>
<td>8</td>
<td>11.6</td>
</tr>
<tr>
<td>16</td>
<td>6.0</td>
</tr>
<tr>
<td>32</td>
<td>5.1</td>
</tr>
</tbody>
</table>
Chapter 4. Hydrodynamic model simulation for November 2009 Mid-Atlantic Nor’easter

4.1 Tidal calibration

Storm tide is a combination of the astronomical tide and the surge associated with a storm. In areas where tidal ranges are relatively high, storm surge can be particularly damaging when it occurs at the time of a high tide. To ensure that the ELCIRC model simulates the long-period wave propagation inside the Chesapeake Bay properly, tidal calibration using the large domain was conducted.

The model was run without salinity and surface wind forcing, only with tidal motion at its open boundary. Thirteen harmonic constituents obtained from the U.S. Army East Coast 2001 database of tidal constituents (Mukai et al., 2002), namely M$_2$, S$_2$, N$_2$, K$_1$, O$_1$, K$_2$, Q$_1$, L$_2$, MU$_2$, NU$_2$, P$_1$, T$_2$, and 2N$_2$, were specified to calculate the water level at each element of the open boundary based on the following formula:

$$\eta(x,y,t) = \sum_i A_i(x,y) f_i(t) \cos [\sigma_i(t-t_0) + V_i(t_0) - \psi_i(x,y)]$$

In the above equation, the amplitude (of constituent $i$) is given by $A_i$, the frequency by $\sigma_i$, the phase by $\psi_i$. The nodal factor is given by $f_i$ and the equilibrium argument by $V_i$. Among these terms, only the frequency $\sigma_i$ is an absolute constant for a given constituent. The amplitudes $A_i$ and phases $\psi_i$ are spatially variable, temporally constant values; the nodal factors $f_i$ and equilibrium arguments $V_i$ are spatially constant, temporally variable values. The latter two terms are essentially important to synchronize model outputs with NOAA observed data.

The tidal simulation started from 10/05/2009 00:00 GMT and spanned 36 days. The first 5 days of running was used to spin up the model. Harmonic analysis was conducted to the last 29 days of hourly model outputs at 11 selected NOAA tidal gauge stations inside the Chesapeake Bay. A
constant Manning coefficient of 0.015 was used to calculate the bottom friction for the entire domain. Predicted tide for the same period at each station was also obtained from the NOAA tide and current website, and analyzed for major tidal constituents as well. The zero phase reference was set to 10/10/2009 00:00 GMT. The locations of the selected NOAA tidal gauge stations are listed in Table 4.1, and shown in Figure 4.1.

Figure 4.1 The locations of 11 selected NOAA tidal gauge stations in the Chesapeake Bay
Table 4.1 Locations of 11 selected NOAA tidal stations

<table>
<thead>
<tr>
<th>Station</th>
<th>Longitude</th>
<th>Latitude</th>
<th>Station</th>
<th>Longitude</th>
<th>Latitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBBT</td>
<td>-76.113</td>
<td>36.967</td>
<td>Solomons</td>
<td>-76.452</td>
<td>38.317</td>
</tr>
<tr>
<td>Sewells Pt.</td>
<td>-76.33</td>
<td>36.947</td>
<td>Cambridge</td>
<td>-76.068</td>
<td>38.573</td>
</tr>
<tr>
<td>Kiptopeke</td>
<td>-75.988</td>
<td>37.167</td>
<td>Annapolis</td>
<td>-76.48</td>
<td>38.983</td>
</tr>
<tr>
<td>Yorktown</td>
<td>-76.478</td>
<td>37.227</td>
<td>Tolchester</td>
<td>-76.245</td>
<td>39.213</td>
</tr>
<tr>
<td>Windmill Pt.</td>
<td>-76.29</td>
<td>37.615</td>
<td>Baltimore</td>
<td>-76.578</td>
<td>39.267</td>
</tr>
<tr>
<td>Lewisetta</td>
<td>-76.465</td>
<td>37.995</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Scatter plots of tidal amplitude and tidal phase between modeled tide and NOAA observed tide for 4 major constituents (M₂, S₂, N₂, and K₁) are shown in Figure 4.2. It can be seen that the ELCIRC model predicts tidal propagation inside the Chesapeake Bay reasonably well. The root-mean-square error (RMS), relative error (E), and correlation coefficient (r) were calculated for error analysis. Mathematical definitions of these statistical measures are shown in Appendix B.

For tidal amplitude comparison, as shown in Figure 4.2 (left panels), the ELCIRC model simulates the amplitude of the dominant tidal constituent M₂ quite well inside the Chesapeake Bay, with the RMS equal to 0.027 m and the correlation coefficient equal to 0.978. As can be seen in Table 4.2, the mean difference between the modeled tide and NOAA observed tide is -0.015 m, and the standard deviation of the difference is 0.023 m, which is 9.5% of the mean tidal amplitude. At most selected tidal gauge stations, the absolute difference is less than 0.02 m, except for Sewells Point, Yorktown, and Cambridge, which have differences of -0.049 m, -0.063 m, and -0.026 m, respectively. In general, stations located along the main channel of the Chesapeake Bay yielded more satisfactory results, while those located in small tributaries of the Bay were likely to have larger discrepancies. This could be explained by the fact the small tributaries require a higher resolution grid to resolve complex shorelines and bathymetry, which posted a challenge for the current model grid being used. For the S₂ constituent, the RMS equals to 0.01 m and the correlation coefficient is 0.887. The mean difference between the modeled tide and NOAA observed tide is -0.007 m, and the standard deviation of the difference is 0.012 m, which is 20.7% of the mean amplitude. Large discrepancies can be found at Sewells Point, Yorktown, and Cambridge. For the constituents of N₂ and K₁, the mean differences between modeled and observed tidal amplitudes are small, 0.009 m and 0.001 m, respectively.
Figure 4.2  Comparison of tidal amplitude (left panel) and tidal phase (right panel) of major tidal constituents between modeled tide and NOAA predicted tide
Table 4.2 Comparison of tidal amplitudes between modeled tide and NOAA observed tide for 4 major tidal constituents at 11 selected tide gauge stations

<table>
<thead>
<tr>
<th>Amplitude</th>
<th>Modeled</th>
<th>NOAA</th>
<th>Diff</th>
<th>Modeled</th>
<th>NOAA</th>
<th>Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBBT</td>
<td>0.353</td>
<td>0.373</td>
<td>-0.020</td>
<td>0.070</td>
<td>0.088</td>
<td>-0.018</td>
</tr>
<tr>
<td>Sewells Pt.</td>
<td>0.311</td>
<td>0.360</td>
<td>-0.049</td>
<td>0.061</td>
<td>0.076</td>
<td>-0.015</td>
</tr>
<tr>
<td>Yorktown</td>
<td>0.267</td>
<td>0.330</td>
<td>-0.063</td>
<td>0.048</td>
<td>0.079</td>
<td>-0.031</td>
</tr>
<tr>
<td>Kiptopeke</td>
<td>0.362</td>
<td>0.381</td>
<td>-0.019</td>
<td>0.074</td>
<td>0.092</td>
<td>-0.018</td>
</tr>
<tr>
<td>Windmill Pt.</td>
<td>0.168</td>
<td>0.172</td>
<td>-0.004</td>
<td>0.038</td>
<td>0.039</td>
<td>-0.001</td>
</tr>
<tr>
<td>Lewisetta</td>
<td>0.197</td>
<td>0.181</td>
<td>0.016</td>
<td>0.058</td>
<td>0.048</td>
<td>0.010</td>
</tr>
<tr>
<td>Solomons</td>
<td>0.172</td>
<td>0.168</td>
<td>0.004</td>
<td>0.051</td>
<td>0.047</td>
<td>0.004</td>
</tr>
<tr>
<td>Cambridge</td>
<td>0.208</td>
<td>0.234</td>
<td>-0.026</td>
<td>0.059</td>
<td>0.068</td>
<td>-0.009</td>
</tr>
<tr>
<td>Annapolis</td>
<td>0.120</td>
<td>0.136</td>
<td>-0.016</td>
<td>0.032</td>
<td>0.036</td>
<td>-0.004</td>
</tr>
<tr>
<td>Tolchester</td>
<td>0.176</td>
<td>0.171</td>
<td>0.005</td>
<td>0.035</td>
<td>0.032</td>
<td>0.003</td>
</tr>
<tr>
<td>Baltimore</td>
<td>0.162</td>
<td>0.156</td>
<td>0.006</td>
<td>0.034</td>
<td>0.031</td>
<td>0.003</td>
</tr>
<tr>
<td>MEAN</td>
<td>0.227</td>
<td>0.242</td>
<td>-0.015</td>
<td>0.051</td>
<td>0.058</td>
<td>-0.007</td>
</tr>
<tr>
<td>STD</td>
<td>-</td>
<td>-</td>
<td>0.023</td>
<td>-</td>
<td>-</td>
<td>0.012</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Amplitude</th>
<th>Modeled</th>
<th>NOAA</th>
<th>Diff</th>
<th>Modeled</th>
<th>NOAA</th>
<th>Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBBT</td>
<td>0.082</td>
<td>0.072</td>
<td>0.010</td>
<td>0.067</td>
<td>0.064</td>
<td>0.003</td>
</tr>
<tr>
<td>Sewells Pt.</td>
<td>0.071</td>
<td>0.064</td>
<td>0.007</td>
<td>0.061</td>
<td>0.053</td>
<td>0.008</td>
</tr>
<tr>
<td>Yorktown</td>
<td>0.061</td>
<td>0.060</td>
<td>0.001</td>
<td>0.055</td>
<td>0.055</td>
<td>0.000</td>
</tr>
<tr>
<td>Kiptopeke</td>
<td>0.082</td>
<td>0.069</td>
<td>0.013</td>
<td>0.074</td>
<td>0.064</td>
<td>0.010</td>
</tr>
<tr>
<td>Windmill Pt.</td>
<td>0.037</td>
<td>0.029</td>
<td>0.008</td>
<td>0.043</td>
<td>0.031</td>
<td>0.012</td>
</tr>
<tr>
<td>Lewisetta</td>
<td>0.042</td>
<td>0.031</td>
<td>0.011</td>
<td>0.029</td>
<td>0.018</td>
<td>0.011</td>
</tr>
<tr>
<td>Solomons</td>
<td>0.038</td>
<td>0.027</td>
<td>0.011</td>
<td>0.028</td>
<td>0.021</td>
<td>0.007</td>
</tr>
<tr>
<td>Cambridge</td>
<td>0.047</td>
<td>0.035</td>
<td>0.012</td>
<td>0.042</td>
<td>0.043</td>
<td>-0.001</td>
</tr>
<tr>
<td>Annapolis</td>
<td>0.028</td>
<td>0.023</td>
<td>0.005</td>
<td>0.045</td>
<td>0.057</td>
<td>-0.012</td>
</tr>
<tr>
<td>Tolchester</td>
<td>0.040</td>
<td>0.031</td>
<td>0.009</td>
<td>0.053</td>
<td>0.069</td>
<td>-0.016</td>
</tr>
<tr>
<td>Baltimore</td>
<td>0.038</td>
<td>0.028</td>
<td>0.010</td>
<td>0.052</td>
<td>0.067</td>
<td>-0.015</td>
</tr>
<tr>
<td>MEAN</td>
<td>0.051</td>
<td>0.043</td>
<td>0.009</td>
<td>0.050</td>
<td>0.049</td>
<td>0.001</td>
</tr>
<tr>
<td>STD</td>
<td>-</td>
<td>-</td>
<td>0.003</td>
<td>-</td>
<td>-</td>
<td>0.010</td>
</tr>
</tbody>
</table>

33
For tidal phase comparison, Figure 4.2 (right panels) suggested that the correlation coefficient is above 0.99 for all 4 major constituents. As can be seen in Table 4.3, the mean difference of tidal phase between modeled tide and NOAA observed tide for M₂, S₂, N₂, K₁ is -4.760°, 17.755°, -14.702° and 25.129°, respectively, and the standard deviation of differences is 9.938°, 14.667°, 10.056° and 13.442°, respectively.

Table 4.3 Comparison of tidal phases between modeled tide and NOAA predicted tide for 4 major tidal constituents at 11 selected tide gauge stations

<table>
<thead>
<tr>
<th>Phase</th>
<th>M₂</th>
<th>NOAA</th>
<th>Diff</th>
<th>Modeled</th>
<th>NOAA</th>
<th>Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBBT</td>
<td>171.832</td>
<td>170.603</td>
<td>1.229</td>
<td>47.186</td>
<td>27.935</td>
<td>19.251</td>
</tr>
<tr>
<td>Sewells Pt.</td>
<td>198.520</td>
<td>196.234</td>
<td>2.286</td>
<td>75.503</td>
<td>54.249</td>
<td>21.254</td>
</tr>
<tr>
<td>Yorktown</td>
<td>204.361</td>
<td>201.109</td>
<td>3.252</td>
<td>86.051</td>
<td>45.119</td>
<td>40.932</td>
</tr>
<tr>
<td>Kiptopeke</td>
<td>186.070</td>
<td>182.108</td>
<td>3.962</td>
<td>62.775</td>
<td>38.454</td>
<td>24.321</td>
</tr>
<tr>
<td>Windmill Pt.</td>
<td>263.241</td>
<td>252.601</td>
<td>10.640</td>
<td>157.848</td>
<td>112.855</td>
<td>44.993</td>
</tr>
<tr>
<td>Lewisetta</td>
<td>321.777</td>
<td>325.705</td>
<td>-3.928</td>
<td>207.547</td>
<td>186.078</td>
<td>21.469</td>
</tr>
<tr>
<td>Solomons</td>
<td>340.790</td>
<td>348.165</td>
<td>-7.375</td>
<td>223.531</td>
<td>211.362</td>
<td>12.169</td>
</tr>
<tr>
<td>Cambridge</td>
<td>29.707</td>
<td>52.799</td>
<td>-23.092</td>
<td>267.825</td>
<td>264.517</td>
<td>3.308</td>
</tr>
<tr>
<td>Annapolis</td>
<td>74.478</td>
<td>81.338</td>
<td>-6.860</td>
<td>302.331</td>
<td>292.458</td>
<td>9.873</td>
</tr>
<tr>
<td>Tolchester</td>
<td>117.871</td>
<td>136.551</td>
<td>-18.680</td>
<td>353.654</td>
<td>355.275</td>
<td>-0.621</td>
</tr>
<tr>
<td>Baltimore</td>
<td>113.017</td>
<td>126.816</td>
<td>-13.799</td>
<td>345.312</td>
<td>345.657</td>
<td>-0.349</td>
</tr>
<tr>
<td>MEAN</td>
<td>183.788</td>
<td>188.548</td>
<td>-4.760</td>
<td>193.539</td>
<td>175.783</td>
<td>17.755</td>
</tr>
<tr>
<td>STD</td>
<td>-</td>
<td>-</td>
<td>9.938</td>
<td>-</td>
<td>-</td>
<td>14.667</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Phase</th>
<th>N₂</th>
<th>NOAA</th>
<th>Diff</th>
<th>Modeled</th>
<th>NOAA</th>
<th>Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBBT</td>
<td>317.468</td>
<td>323.656</td>
<td>-6.188</td>
<td>271.811</td>
<td>239.712</td>
<td>32.099</td>
</tr>
<tr>
<td>Sewells Pt.</td>
<td>344.003</td>
<td>351.287</td>
<td>-7.284</td>
<td>285.495</td>
<td>253.371</td>
<td>32.124</td>
</tr>
<tr>
<td>Yorktown</td>
<td>349.047</td>
<td>363.045</td>
<td>-13.998</td>
<td>288.138</td>
<td>247.287</td>
<td>40.851</td>
</tr>
<tr>
<td>Kiptopeke</td>
<td>330.840</td>
<td>334.757</td>
<td>-3.917</td>
<td>278.320</td>
<td>246.029</td>
<td>32.291</td>
</tr>
<tr>
<td>Windmill Pt.</td>
<td>46.712</td>
<td>47.755</td>
<td>-1.043</td>
<td>313.326</td>
<td>269.866</td>
<td>43.460</td>
</tr>
<tr>
<td>Lewisetta</td>
<td>106.149</td>
<td>117.451</td>
<td>-11.302</td>
<td>354.053</td>
<td>313.738</td>
<td>40.315</td>
</tr>
<tr>
<td>Solomons</td>
<td>125.536</td>
<td>136.519</td>
<td>-10.983</td>
<td>30.868</td>
<td>16.877</td>
<td>13.991</td>
</tr>
<tr>
<td>Cambridge</td>
<td>172.440</td>
<td>204.888</td>
<td>-32.448</td>
<td>53.437</td>
<td>40.433</td>
<td>13.004</td>
</tr>
<tr>
<td>Annapolis</td>
<td>214.807</td>
<td>235.408</td>
<td>-20.601</td>
<td>65.629</td>
<td>57.694</td>
<td>7.935</td>
</tr>
<tr>
<td>Tolchester</td>
<td>254.861</td>
<td>283.428</td>
<td>-28.567</td>
<td>74.409</td>
<td>61.906</td>
<td>12.503</td>
</tr>
<tr>
<td>Baltimore</td>
<td>250.323</td>
<td>275.710</td>
<td>-25.387</td>
<td>75.736</td>
<td>67.891</td>
<td>7.845</td>
</tr>
<tr>
<td>MEAN</td>
<td>228.381</td>
<td>243.082</td>
<td>-14.702</td>
<td>190.111</td>
<td>164.982</td>
<td>25.129</td>
</tr>
<tr>
<td>STD</td>
<td>-</td>
<td>-</td>
<td>10.056</td>
<td>-</td>
<td>-</td>
<td>13.442</td>
</tr>
</tbody>
</table>
Overall, the tidal simulation is satisfactory when compared with NOAA observed tide. It suggests that the ELCIRC model is capable of simulating the characteristics of long-period wave propagating inside the Chesapeake Bay.

4.2 Evaluation of forecast winds

Meteorological records were directly obtained from the NOAA tide and current website for the period of 11/10/2009 00:00 GMT to 11/16/2009 00:00 GMT. Figure 4.3 through Figure 4.9 compare the 6-day time series of forecast winds with observed wind at 7 selected NOAA stations. The observational data suggested that the November 2009 Mid-Atlantic Nor’easter featured strong, consistent northeast wind over the entire Chesapeake Bay region, with variations subject to local controls. The evaluations of wind speed and wind direction were done separately. Figure 4.10 compares the wind speed between observed and predicted winds, and Figure 4.11 compares the wind direction. It can be seen that the wind direction was predicted very well by all forecast winds, but the wind speed at certain stations, especially the middle-Bay stations, tended to be over-predicted. Further evaluation of each forecast wind was conducted by calculating its statistical measures, as shown in Table 4.4.
Figure 4.5  Time-series comparison of wind velocity at Lewisetta

Figure 4.6  Time-series comparison of wind velocity at Solomons

Figure 4.7  Time-series comparison of wind velocity at Cambridge

Figure 4.8  Time-series comparison of wind velocity at Tolchester
Overall, the behavior of the NAM forecast wind was acceptable. It compared reasonably well with meteorological records at most stations, except at Chesapeake Bay Bridge Tunnel (CBBT), Kiptopeke, and Tolchester. At CBBT, it under-predicted the wind speed slightly, especially during the peak time of 11/12/09 to 11/13/09. At Kiptopeke and Tolchester, it captured the overall trends of wind speed, but tended to over-predict significantly. Statistical measures of the NAM wind, including the root-mean-square error (RMS), the relative error (E), the correlation coefficient (r), and the model skill relative error, were calculated at each station and listed in Table 4.4. It was shown that the relative errors at Kiptopeke and Tolchester were rather large, reaching 41.23% and 74.07%, respectively. The average skill score of the NAM forecast wind is only 0.82.

The WRF-GFS regional forecast wind, which has both higher temporal and spatial resolutions than the GFS global forecast wind, compared favorably with observational data throughout the Chesapeake Bay. In particular, the predictions at CBBT and Baltimore were superior. At these two stations, the RMS and relative error of the WRF-GFS were relatively low compared to those of the other forecast winds. However, considerably large discrepancies can be found at Kiptopeke and Tolchester as well, where the relative error reached 41.23% and 74.07%, respectively. The
average skill score of the WRF-GFS forecast wind is 0.81. Generally speaking, the predictive skills of the NAM forecast wind and the WRF-GFS wind are comparable.

The RAMS-GFS forecast wind, which has a very fine resolution of 2 km, is considered to be the most reliable wind in this study. Its wind fields compared notably well with observational data at most stations, where other forecast winds tended to have larger discrepancies. At Baltimore, the RAMS-GFS wind slightly under-predicted the wind speed, but still had an RMS of 1.91 m and a relative error of 26.16%. Statistical measures of the RAMS-GFS wind in Table 4.4 also suggest that this wind was generally more reliable than the other forecast winds. The average skill score of the RAMS-GFS wind reached as high as 0.87.

Table 4.4 Comparison of wind speed between observed and predicted winds at 7 NOAA stations

<table>
<thead>
<tr>
<th></th>
<th>RMS</th>
<th>E</th>
<th>r</th>
<th>skill</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBCT</td>
<td>2.86</td>
<td>9.43</td>
<td>0.97</td>
<td>0.95</td>
</tr>
<tr>
<td>Kiptopeke</td>
<td>5.15</td>
<td>41.23</td>
<td>0.86</td>
<td>0.75</td>
</tr>
<tr>
<td>Lewisetta</td>
<td>3.20</td>
<td>26.37</td>
<td>0.93</td>
<td>0.85</td>
</tr>
<tr>
<td>Solomons</td>
<td>2.63</td>
<td>19.90</td>
<td>0.93</td>
<td>0.89</td>
</tr>
<tr>
<td>Cambridge</td>
<td>2.27</td>
<td>13.39</td>
<td>0.94</td>
<td>0.93</td>
</tr>
<tr>
<td>Tolchester</td>
<td>4.88</td>
<td>74.07</td>
<td>0.69</td>
<td>0.44</td>
</tr>
<tr>
<td>Baltimore</td>
<td>1.67</td>
<td>14.19</td>
<td>0.94</td>
<td>0.92</td>
</tr>
<tr>
<td>AVERAGE</td>
<td>3.24</td>
<td>28.37</td>
<td>0.89</td>
<td>0.82</td>
</tr>
<tr>
<td>WRF-GFS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBCT</td>
<td>1.87</td>
<td>3.62</td>
<td>0.97</td>
<td>0.98</td>
</tr>
<tr>
<td>Kiptopeke</td>
<td>5.18</td>
<td>40.72</td>
<td>0.88</td>
<td>0.75</td>
</tr>
<tr>
<td>Lewisetta</td>
<td>3.33</td>
<td>27.91</td>
<td>0.93</td>
<td>0.84</td>
</tr>
<tr>
<td>Solomons</td>
<td>3.07</td>
<td>23.88</td>
<td>0.93</td>
<td>0.87</td>
</tr>
<tr>
<td>Cambridge</td>
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<td>10.70</td>
<td>0.96</td>
<td>0.94</td>
</tr>
<tr>
<td>Tolchester</td>
<td>6.05</td>
<td>79.77</td>
<td>0.66</td>
<td>0.38</td>
</tr>
<tr>
<td>Baltimore</td>
<td>1.29</td>
<td>11.30</td>
<td>0.92</td>
<td>0.94</td>
</tr>
<tr>
<td>AVERAGE</td>
<td>3.24</td>
<td>28.27</td>
<td>0.89</td>
<td>0.81</td>
</tr>
<tr>
<td>RAMS-GFS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBCT</td>
<td>2.78</td>
<td>8.36</td>
<td>0.95</td>
<td>0.96</td>
</tr>
<tr>
<td>Kiptopeke</td>
<td>2.60</td>
<td>26.38</td>
<td>0.85</td>
<td>0.86</td>
</tr>
<tr>
<td>Lewisetta</td>
<td>1.46</td>
<td>9.01</td>
<td>0.93</td>
<td>0.95</td>
</tr>
<tr>
<td>Solomons</td>
<td>1.83</td>
<td>16.84</td>
<td>0.91</td>
<td>0.91</td>
</tr>
<tr>
<td>Cambridge</td>
<td>1.44</td>
<td>8.04</td>
<td>0.95</td>
<td>0.96</td>
</tr>
<tr>
<td>Tolchester</td>
<td>2.96</td>
<td>59.31</td>
<td>0.71</td>
<td>0.60</td>
</tr>
<tr>
<td>Baltimore</td>
<td>1.91</td>
<td>26.16</td>
<td>0.90</td>
<td>0.85</td>
</tr>
<tr>
<td>AVERAGE</td>
<td>2.14</td>
<td>22.01</td>
<td>0.89</td>
<td>0.87</td>
</tr>
</tbody>
</table>
Figure 4.10 Comparison of wind speed between NOAA meteorological records and forecast winds at 7 NOAA stations
Figure 4.11 Comparison of wind direction between NOAA meteorological records and forecast winds at 7 NOAA stations
As suggested by scatter plots in Figure 4.12 to Figure 4.18, overall, all forecast winds employed in this study showed reasonable predictive skill during the November 2009 Mid-Atlantic Nor’easter. The RAMS-GFS wind was by far the most reliable wind available. This wind performed consistently well over the entire Bay, and had the lowest average RMS and relative error of all forecast winds. Inclusion of the NAM wind and WRF-GFS wind, on the other hand, did not yield satisfactory results at certain stations, especially in the middle- and upper-Bay. But their overall performances were acceptable.

It should be noted that most tidal stations are located at water-land margins, where the wind fields are more complex than those of the open water. When wind is blowing from land to water, a higher surface roughness over land would reduce the wind velocity significantly. A careful examination of the wind fields at Kiptopeke and Tolchester suggested that the observed wind speeds were significantly weaker than those predicted. One possible explanation for this phenomenon is that, during the 2009 November Mid-Atlantic Nor’easter when the northeast wind was dominant, meteorological sensors at these stations were blocked from receiving the NE wind by land. For more accurate assessment of forecast winds in the future, more stations should be included. Therefore, a definite conclusion for the forecast winds evaluation would be hard to draw. Based on current evidence, the RAMS-GFS wind with the highest resolution seemed to perform better than either the NAM wind or the WRF-GFS wind. However, it is our belief that each forecast wind is sufficient to be used as external forcing in the hydrodynamic ELCIRC model for storm surge and inundation predictions. In particular, once the ensemble ocean forecast approach is evoked, accurate water level simulations would be expected.

![Figure 4.12 Scatter plot of wind speed at CBBT](image1)

![Figure 4.13 Scatter plot of wind speed at Kiptopeke](image2)
Figure 4.14  Scatter plot of wind speed at Lewisetta

Figure 4.15  Scatter plot of wind speed at Solomons

Figure 4.16  Scatter plot of wind speed at Cambridge

Figure 4.17  Scatter plot of wind speed at Tolchester

Figure 4.18  Scatter plot of wind speed at Baltimore
4.3 Storm tide and inundation simulation

Once the ELCIRC model had been properly calibrated with tide, external forcings were applied in the model to simulate storm surge and inundation inside the Chesapeake Bay during severe storms. As the water level fluctuations in the Bay depend critically on the meteorological conditions, forecast wind and pressure fields with higher accuracy are supposed to let the ELCIRC hydrodynamic model yield better predictions. However, in reality, a weather forecast is made in real time, and thus cannot be evaluated prior to the coming of the storm event. To deal with uncertainty associated with different meteorological forecasts, ensemble storm surge forecast was brought up and put into practice. In this study, 3 sets of forecast winds (the NAM forecast wind, the WRF-GFS forecast wind, and the RAMS-GFS forecast wind) were employed to drive the ELCIRC model simultaneously in order to simulate the Bay’s response to the November 2009 Mid-Atlantic Nor’easter. A 5-minute time step was used in this application of the model.

4.3.1 Storm tide simulation for the Chesapeake Bay

After each individual run finished, the ensemble average was calculated by taking the mean of all members. The main purpose of this section is to investigate and report how the ELCIRC hydrodynamic model would behave under different meteorological forcings, and to assess its overall predictive skill during the November 2009 Mid-Atlantic Nor’easter.

Water level response to the storm was examined at 11 NOAA tide gauge stations inside the Chesapeake Bay. The time-series comparison of simulated and observed water levels, along with model discrepancy analysis at each station, are given in Figure 4.19 through Figure 4.29. Statistical measures, including the RMS, relative errors, correlation coefficients and skill scores (refer to Appendix B), were also calculated for the error analysis of model results, shown in Table 4.5.
## Table 4.5 Statistical measures of predicted water levels at 11 NOAA tidal gauge stations

<table>
<thead>
<tr>
<th>NOAA Stations</th>
<th>RMS</th>
<th>E</th>
<th>r</th>
<th>skill</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBBT</td>
<td>0.11</td>
<td>1.63</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Sewells Pt.</td>
<td>0.10</td>
<td>1.32</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Kiptopeke</td>
<td>0.10</td>
<td>1.75</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Yorktown</td>
<td>0.09</td>
<td>1.62</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Windmill Pt.</td>
<td>0.07</td>
<td>1.88</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Lewisetta</td>
<td>0.14</td>
<td>9.39</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td>Solomons</td>
<td>0.16</td>
<td>16.09</td>
<td>0.90</td>
<td>0.92</td>
</tr>
<tr>
<td>Cambridge</td>
<td>0.19</td>
<td>18.45</td>
<td>0.87</td>
<td>0.90</td>
</tr>
<tr>
<td>Annapolis</td>
<td>0.19</td>
<td>25.22</td>
<td>0.83</td>
<td>0.86</td>
</tr>
<tr>
<td>Tolchester</td>
<td>0.21</td>
<td>22.17</td>
<td>0.87</td>
<td>0.88</td>
</tr>
<tr>
<td>Baltimore</td>
<td>0.21</td>
<td>25.13</td>
<td>0.85</td>
<td>0.86</td>
</tr>
<tr>
<td><strong>AVERAGE</strong></td>
<td><strong>0.14</strong></td>
<td><strong>11.33</strong></td>
<td><strong>0.93</strong></td>
<td><strong>0.94</strong></td>
</tr>
</tbody>
</table>

### NAM

| CBBT          | 0.10 | 1.50 | 0.99 | 0.99  |
| Sewells Pt.   | 0.11 | 1.54 | 0.99 | 0.99  |
| Kiptopeke     | 0.11 | 2.09 | 0.99 | 0.99  |
| Yorktown      | 0.12 | 2.50 | 0.98 | 0.99  |
| Windmill Pt.  | 0.07 | 1.85 | 0.98 | 0.99  |
| Lewisetta     | 0.12 | 7.38 | 0.97 | 0.96  |
| Solomons      | 0.15 | 15.65| 0.93 | 0.92  |
| Cambridge     | 0.23 | 28.38| 0.82 | 0.84  |
| Annapolis     | 0.23 | 36.04| 0.78 | 0.80  |
| Tolchester    | 0.25 | 33.47| 0.82 | 0.81  |
| Baltimore     | 0.24 | 34.46| 0.81 | 0.81  |
| **AVERAGE**   | **0.16** | **14.99** | **0.91** | **0.92** |

### WRF-GFS

| CBBT          | 0.12 | 1.89 | 0.99 | 0.99  |
| Sewells Pt.   | 0.11 | 1.49 | 0.99 | 0.99  |
| Kiptopeke     | 0.11 | 2.09 | 0.99 | 0.99  |
| Yorktown      | 0.11 | 2.29 | 0.98 | 0.99  |
| Windmill Pt.  | 0.09 | 2.65 | 0.99 | 0.99  |
| Lewisetta     | 0.10 | 4.66 | 0.97 | 0.98  |
| Solomons      | 0.12 | 8.54 | 0.94 | 0.96  |
| Cambridge     | 0.16 | 12.25| 0.92 | 0.94  |
| Annapolis     | 0.14 | 13.70| 0.92 | 0.93  |
| Tolchester    | 0.16 | 14.34| 0.93 | 0.92  |
| Baltimore     | 0.15 | 13.70| 0.92 | 0.93  |
| **AVERAGE**   | **0.12** | **7.05** | **0.96** | **0.96** |

### RAMS-GFS

| CBBT          | 0.09 | 1.14 | 0.99 | 0.99  |
| Sewells Pt.   | 0.08 | 0.83 | 0.99 | 1.00  |
| Kiptopeke     | 0.09 | 1.50 | 0.99 | 0.99  |
| Yorktown      | 0.09 | 1.34 | 0.99 | 0.99  |
| Windmill Pt.  | 0.06 | 1.19 | 0.99 | 0.99  |
| Lewisetta     | 0.10 | 5.18 | 0.97 | 0.97  |
| Solomons      | 0.13 | 11.03| 0.94 | 0.94  |
| Cambridge     | 0.17 | 16.26| 0.89 | 0.91  |
| Annapolis     | 0.17 | 21.05| 0.88 | 0.89  |
| Tolchester    | 0.19 | 19.61| 0.90 | 0.89  |
| Baltimore     | 0.18 | 20.09| 0.89 | 0.89  |
| **AVERAGE**   | **0.12** | **9.02** | **0.95** | **0.95** |
For storm tides generated by the NAM wind, as shown by the green lines in Figure 4.19 to Figure 4.29, it can be seen that the simulated water levels at the Lower Bay stations, including CBBT, Kiptopeke, Sewells Point, Yorktown, and Windmill Pt., were rather accurate. Model discrepancies suggested frequent fluctuations, especially during surge peaks when wind speed was strong, but were generally within 0.3 m. From the middle Bay towards the Upper Bay, however, simulated water levels at Lewisetta, Solomons Island, Cambridge, Annapolis, Tolchester, and Baltimore were rather unsatisfactory. Observed water levels at these stations suggested a short period of set-down before a prolonged period of set-up. These phenomena were very different from what we saw at the Lower Bay stations, where much more rapid water responses were seen, and the water level peaked significantly during strong wind. The ELCIRC model over-estimated the set-down at the middle and Upper Bay stations, and the total water level was generally under-predicted from 11/11/2009 12:00 GMT to 11/13/2009 12:00 GMT.

Statistical measures of model results are shown in Table 4.5. The RMS error is within 0.11 m in the Lower Bay and 0.21 m in the middle and Upper Bay, which gives an average RMS error of 0.14 m for the entire Bay. Also, the relative error increased from less than 2% in the Lower Bay to more than 25% in the Upper Bay, giving the average relative error of 11.33%. The mean correlation coefficient and the mean skill score of the NAM wind are 0.93 and 0.94, respectively.

The storm tides generated by the WRF-GFS wind, as shown by the cyan lines in Figure 4.19 through Figure 4.29, seem to have higher accuracy in the Lower and Middle Bay, but lower accuracy in the Upper Bay, compared to those of the NAM wind. At CBBT, Sewells Pt., Kiptopeke, Yorktown, and Windmill Pt., model simulations tended to over-predict the surge slightly. At the Upper Bay stations, however, water level was significantly under-predicted for a prolonged period of time. In general, the model discrepancy is within 0.5 m. Statistical measures of simulated water level yielded from the WRF-GFS wind in Table 4.5 also verified our findings in the time-series plots. The RMS errors in the Lower and Middle Bay are comparable with those of the NAM wind, generally within 0.12 m, but are much larger in the Upper Bay, reaching 0.25 m. This is consistent with what we found in the previous section of wind evaluation: the quality of the WRF-GFS wind is higher in the Lower Bay and lower in the Upper Bay. In general, the average RMS, average relative error, average correlation coefficient, and average skill score is 0.16 m, 14.99%, 0.91, and 0.92, respectively. The overall model performance using the WRF-GFS wind is not as good as that using the NAM wind, but is still acceptable.
The storm tide generated by the RAMS-GFS wind, as shown in Figure 4.19 through Figure 4.29 by the blue lines, is by far the most accurate model results available. The simulated water level matched the observations well at most stations throughout the Bay. At the Lower Bay stations, the model discrepancy still fluctuated heavily during the surge peak, but was generally within 0.2 m, smaller than those of the NAM wind and the WRF-GFS wind. At the Upper Bay stations, total water level was under-predicted during the set-up, but to a lesser extent. Statistical measures shown in Table 4.5 also suggested that the simulated water level yielded from the RAMS-GFS wind has the highest accuracy. The RMS is within 0.12 m at the lower and middle Bay stations, and within 0.16 m at the Upper Bay stations, giving an average RMS of 0.12 m. The average relative error is 7.05%, and the average skill score is as high as 0.96, suggesting a satisfactory performance of the ELCIRC model on storm tide prediction using the RAMS-GFS wind.

Based on the analysis of each individual result, it is believed that the predictive skill of the ELCIRC hydrodynamic model is consistent with the quality of each forecast wind being employed. In other words, a better storm tide prediction would be expected if a more reliable forecast wind were used.

The ensemble average of time-series water level was also calculated by taking the mean of all its members, as shown by the black lines in Figure 4.19 through Figure 4.29. It can be seen that the ensemble average fell within its ensemble spreads, and its discrepancy was reduced at Lower Bay stations. At middle and Upper Bay stations, the accuracy of the ensemble average was not significantly improved due to its low quality members, which were model results generated by the NAM wind and the WRF-GFS wind. Statistical measures of the ensemble average are also shown in Table 4.5. The RMS is within 0.09 m at the Lower Bay stations, suggesting a noticeable improvement in model accuracy in the Lower Bay area. Examination of other statistical measures, including the relative error, the correlation coefficient, and the skill score, also led to the same conclusion.
Figure 4.19  Comparison between simulated and observed water levels (upper panel) along with model discrepancies (lower panel) at CBBT

Figure 4.20  Comparison between simulated and observed water levels (upper panel) along with model discrepancies (lower panel) at Sewells Pt.

Figure 4.21  Comparison between simulated and observed water levels (upper panel) along with model discrepancies (lower panel) at Kiptopeke
Figure 4.22  Comparison between simulated and observed water levels (upper panel) along with model discrepancies (lower panel) at Yorktown

Figure 4.23  Comparison between simulated and observed water levels (upper panel) along with model discrepancies (lower panel) at Windmill Pt.

Figure 4.24  Comparison between simulated and observed water levels (upper panel) along with model discrepancies (lower panel) at Lewisetta
Figure 4.25  Comparison between simulated and observed water levels (upper panel) along with model discrepancies (lower panel) at Solomons

Figure 4.26  Comparison between simulated and observed water levels (upper panel) along with model discrepancies (lower panel) at Cambridge

Figure 4.27  Comparison between simulated and observed water levels (upper panel) along with model discrepancies (lower panel) at Annapolis

49
Based on our previous assessment of each individual run and their ensemble average, it was determined that calculating the ensemble approach may not inevitably yield the best result under all conditions, and should be used with caution. To better illustrate this idea, bar graphs of RMS error are shown in Figure 4.30. It can be seen that the RMS increased from the Lower Bay to the Upper Bay, suggesting the growth of model discrepancies for all individual results. This is consistent with our previous findings. Figure 4.30 also shows that the ensemble average has the lowest RMS at the Lower Bay stations, but not the Upper Bay stations. In the Lower Bay area, where all forecast winds seemed to have generated reasonable storm surge and model discrepancies showed random fluctuations, calculating the ensemble average could yield a better
result by reducing model uncertainty. However, in the Upper Bay area, only the RAMS-GFS wind has yielded good results and the others did not. Under this circumstance, calculating the ensemble average would not necessarily reduce the overall error.

![Figure 4.30](image.jpg)

In general, the ensemble ocean forecast technique showed certain merits in reducing model uncertainty, and improved the performance of the ELCIRC model in general. The model simulated the storm tide reasonably well, especially at the lower-Bay stations. Discrepancies were found at middle and Upper Bay stations, where total water levels were notably under-predicted from 11/11/2009 12:00 GMT to 11/13/2009 12:00 GMT. There is a strong indication that this phenomenon might be caused by the over-estimation of surface wind stress in the Upper Bay area, which induced the local set-down.

4.3.2 Influence of fetch-limited wind drag coefficient on water level fluctuation in the Upper Bay

Storm tide simulations results reported in Section 4.3.1 suggest that the water level was notably under-predicted in the Upper Bay region. More effort was made in this section in an attempt to improve the model results. In order to identify the mechanisms that account for the model discrepancy in the Upper Bay, three hypotheses were made: (1) It was suspected that the
discrepancy was attributed to the inadequate representation of hydrodynamics in the C&D canal (see Figure 4.31) that connects the Chesapeake Bay and the Delaware Bay. After a careful examination of the water level and flow field at NOAA station Reedy Point, however, it was found that the total volume transport through the canal was too small to have a major impact on the water level fluctuation in the Upper Bay. (2) It was also suspected that the discrepancy was due to the imperfection of the predicted wind fields in the Upper Bay area. Evaluations of forecast winds in Section 4.2 suggest that there was a slight tendency of over-estimation of wind speed at certain Upper Bay stations. However, this error could also come from bias in the meteorological observations. Given the fact that all forecast winds tended to under-predict the water level in the Upper Bay, other factors other than the predicted wind itself could be the cause of the discrepancy. (3) It was suspected that the parameterization of surface wind drag coefficient in the Upper Bay area was not appropriate. In this study, the drag coefficient $C_d$ used in the ELCIRC model was determined based on Large and Pond’s (1981) formula:

$$C_d = (a + b|\bar{W}|) \times 10^{-3}$$

with the empirical parameters $a=0.49$ and $b=0.065$. Large and Pond’s formula (hereafter, LP formula) in calculating $C_d$ is generally valid for the open ocean, especially during moderate wind. However, in the fetch-limited areas, such as lakes and semi-enclosed basins, parameterization of $C_d$ should also consider the presence and the state of the surface waves. The wave field is fundamental because it controls the amount of momentum being transferred into the water and its vertical distribution within the surface boundary layer. The upper Chesapeake Bay, from north of the Patuxent River to the Susquehanna River flat (see Figure 4.32), in essence is a fetch-limited area with only one major outlet connected to the Lower Bay in the south. Due to the limited horizontal extent of the Upper Bay, the wave-induced complexity is more pronounced than that of the open ocean, in which quasi-steady conditions are more easily obtained. Further investigations on the parameterization of fetch-limited wind drag coefficient and its influence on the total water level fluctuation in the Upper Bay area were conducted below.
Figure 4.31 Illustration of C&D canal in the high-resolution small domain grid
Figure 4.32  The fetch-limited Upper Bay area (shown in yellow)
Wave dependency of wind-induced stress

The mechanism by which waves influence on the air/water coupling is such that the wave profile produces additional roughness, thereby increasing the friction and enhancing the momentum flux from the air to the water. The amount of momentum flux depends on the significant wave height $H_{1/3}$ or on the steepness $H_{1/3}/\lambda$ of the waves. A large number of measurements have been carried out to quantify the wave effect on the wind drag coefficient. Figure 4.33 (a) shows the data collected predominantly in the lake and reservoirs by various measurement techniques, including the profile method (fitting logarithmic vertical profiles to measured wind velocity), the direct method (measuring the stress), and the dissipation method by determining dissipation of turbulent kinetic energy (TKE) in the inertial sub-range, were reviewed by Wuest and Lorke (2003). Despite the large scatter, it is relatively clear that the drag coefficient depends, to a large extent, on wind speed and on the wave development state as well. From these two factors, one must first consider the situation of developed waves at different wind speeds. There are basically two ranges to be described independently: wind larger than 5 m/s and wind below 5 m/s. For strong winds (>5 m/s) the surface roughness is determined by the height of the gravity waves, and subsequently, friction is dominated by those waves. Charnock (1955) found the relation between wind speed, height of measurement, and the wave height scale. Introducing the Charnock relation into the wind stress equation, the $C_d$ relation was obtained and plotted in Figure 4.33 (a). The theoretical result was excellent, but the procedure is questionable because the conversion of roughness height $Z_0$ can generate large uncertainties. The uncertainties of a factor of 10 in $Z_0$ translate to uncertainties of a factor of 2 in $C_d$.

For weak winds (<5 m/s) the influence of gravity waves on surface stress eases, and the surface tension or small-scale capillary waves-generated “virtual” roughness become increasingly important (Wu, 1994). At low wind speed (<3 m/s), the experimental values of $C_d$ (Yelland and Taylor, 1996; Bradley et al., 1991; Simon et al., 2002) consistently increase faster with decreasing wind. Astonishingly enough, such weak winds can have drag coefficients larger than those for 25 m/s winds. In Figure 4.33 (a), the surprising result of the comparison of the low- and high-wind regime reveals that there is a minimum drag coefficient at approximately 4-5 m/s. This is very different from the open ocean result represented by Garratt (1977) and Large and Pond (1981), shown as the dotted line in Figure 4.33 (b).
Figure 4.33  Wind-drag coefficients $C_d$ as function of wind speed at 10-m height

(a) Wuest and Lorke (2003)

(b) Lin, Sanford, and Suttles (2002)
The revised wind drag coefficient formula for the Upper Bay

Lin, Sanford and Suttles (2002) (hereafter, LSS formula) conducted a fetch-limited wind wave experiment at the mouth of the Choptank River in the Upper Chesapeake Bay. The turbulent Reynolds stress, wind speed, direction, air temperature, wave period, and velocity component were first measured. The data were then carefully selected through a QA/QC procedure and the result of the wind drag coefficient versus the value of $U_{10}$ was shown in Figure 4.33 (b). The data obtained from the Upper Bay were shown as open circles and fitted by a solid line whereas the data obtained by Donelan (1990) from the open ocean measurement were shown as solid squares and fitted with a dotted line, for comparison.

It is interesting to observe that the pattern of the data collected by LSS in the Upper Bay is more similar to the relationship obtained for the fetch-limited inland lake than that obtained for the open ocean. It possesses a pattern similar to that of a minimum drag coefficient, with a wind speed of around 4-5 m/s. For wind speeds less than 3 m/s, it also shows a rapid increase of the wind drag coefficient as the wind speed is reduced. For wind speeds larger than 4-5 m/s, the slope of the dependence of the wind drag coefficient on wind speeds is less steep as compared with that under the oceanic condition. In fact, the LSS data have the least slope of $C_d$ versus $U_{10}$ for $U_{10}$ values exceeding 5 m/s among all the data presented under different environmental conditions (ocean, lakes, reservoirs, and estuarine water). Whether this is due to the special condition in the estuarine water, such as the presence of the strong stratification and its effect on the small-scale turbulence, is unknown and yet to be determined by future research. If the LSS data were extrapolated from $U_{10}$ values ranging from 10 m/s to 20 m/s, this can translate to a factor-of-2 difference on the value of $C_d$ obtained, which is precisely the uncertainty that exists in the Charnock relationship due to the uncertainty from the estimation of $Z_0$.

Given the understanding of the above relation, a different wind drag coefficient relationship can be generated for the fetch-limited condition in the Upper Bay. A revised wind-drag coefficient formula based on LSS formula (Lin et al., 2002) is given by

$$C_d = (0.643 + 0.0467|W|) \times 10^{-3}.$$
which was adopted in the region of the Upper Bay north of the Patuxent River. For the remainder of the domain spanning the coastal ocean and the Lower Bay, the LP formula was still used in the revised storm surge simulation for the November 2009 Northeaster. The use of the LP formula is justifiable because, in the Lower Bay, a larger area is available for the wind fetch and the propagation of the swell through the Bay mouth into the Lower Bay more resembles the coastal ocean condition. As it was found that during the Hurricane wind there is a reduction of wind drag coefficient (Powell et al., 2003), we assume that there is a maximum cap for the wind drag coefficient $C_d$ under a constant value of 0.0011 when the wind is exceeding 12 m/s from the northeast.

Using the LSS formula and the cap for maximum wind drag coefficient in the Upper Bay area, the simulated waters level at the Upper Bay stations were greatly improved. Figure 4.34 through Figure 4.36 show examples of the simulation results at Annapolis, Tolchester, and Baltimore. In these figures, the baselines are the results obtained by the LP formula in the previous simulation whereas the results of using the reduced drag coefficient are the results obtained by LSS revised formula. The wind stress calculated based on the LSS formula and the cap used in the Upper Bay creates a reduction of about 50% of wind stress compared to that calculated by the LP formula in the high wind regime (above 10 m/s). Responding to the wind stress, the water levels in the Upper Bay produce less set-down and bounce back with the most change occurring at Tolchester followed by Baltimore and Annapolis. For the wind speed below 10 m/s outside the strong northeaster period, the LSS and LP formula converge to the similar wind drag coefficient with each other and the associated water level was less affected. It is noted that the fetch-limited effect is most profound near the head of the Bay and gradually decreasing from the north to the south and ends in the mid-Chesapeake Bay area. It is evident that the under-prediction of the water level in the previous simulation was due to the overestimation of the wind drag coefficient in the Upper Bay. Once the wind drag coefficient was revised, the prediction skill for the water level became much improved in the Upper Bay using the fetch-limited wind drag formula during the northeaster event in November 2009. The results met our expectation, and certainly proved possible merits in our hypothesis.
Figure 4.34  Simulated water level with revised wind drag coefficient in the Upper Bay against baseline at Annapolis

Figure 4.35  Simulated water level with revised wind drag coefficient in the Upper Bay against baseline at Tolchester

Figure 4.36  Simulated water level with revised wind drag coefficient in the Upper Bay against baseline at Baltimore
When the fetch-limited wind drag formula was only applied from 11/11/2009 12:00 GMT to 11/13/2009 12:00 GMT in the storm surge simulation, model results were even better compared to the baseline, as shown in Figure 4.37 through Figure 4.39. The RMS errors were calculated at each station and shown in bar graphs in Figure 4.40, which obviously suggests a significant improvement on water level prediction in the Upper Bay.

![Simulated water level with revised wind drag coefficient being applied for a constrained period of time in the Upper Bay against baseline at Annapolis](image)

**Figure 4.37** Simulated water level with revised wind drag coefficient being applied for a constrained period of time in the Upper Bay against baseline at Annapolis

![Simulated water level with revised wind drag coefficient being applied for a constrained period of time in the Upper Bay against baseline at Tolchester](image)

**Figure 4.38** Simulated water level with revised wind drag coefficient being applied for a constrained period of time in the Upper Bay against baseline at Tolchester

![Simulated water level with revised wind drag coefficient being applied for a constrained period of time in the Upper Bay against baseline at Baltimore](image)

**Figure 4.39** Simulated water level with revised wind drag coefficient being applied for a constrained period of time in the Upper Bay against baseline at Baltimore
4.3.3 Inundation simulation in the Lower Bay

One superior feature of the ELCIRC model is its natural handling of wetting-and-drying, which allows it to simulate coastal inundation robustly and accurately. Before the November 2009 Mid-Atlantic Nor’easter caused a major flooding along the coast, the United States Geological Survey (USGS) rapidly deployed 9 water level sensors in the Greater Hampton Roads area to measure coastal floods from 11/12/2009 to 11/15/2009 (locations of these sensors can be found in Table 4.6). Determination of water-level elevation (McGee et al., 2008) requires 1) correcting water-level sensor pressure for barometric pressure to obtain difference in pressure; 2) converting the difference in pressure to the height of water above sensor; and 3) converting the height of water above the sensor to elevation of water above the reference datum, in this case, the North American Vertical Datum 1988 (NAVD88). A value of #N/A indicates that the water level fell below the threshold elevation of the sensor, which is defined as 0.07 feet (0.021m) above the sensor membrane. The resultant quality-controlled flood elevation data were quickly uploaded to a repository website, and shared by government officials and CIPS partners.
Table 4.6 Locations of 9 water-level sensors deployed by USGS

<table>
<thead>
<tr>
<th>USGS Sensor</th>
<th>Longitude</th>
<th>Latitude</th>
<th>Selected for comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>Messick</td>
<td>-76.319167</td>
<td>37.110556</td>
<td>1</td>
</tr>
<tr>
<td>Poquoson</td>
<td>-76.375833</td>
<td>37.141944</td>
<td>2</td>
</tr>
<tr>
<td>Langley</td>
<td>-76.393056</td>
<td>37.108611</td>
<td>3</td>
</tr>
<tr>
<td>Seaford</td>
<td>-76.396944</td>
<td>37.178333</td>
<td>4</td>
</tr>
<tr>
<td>Gwynns</td>
<td>-76.310000</td>
<td>37.492778</td>
<td>--</td>
</tr>
<tr>
<td>Lesner</td>
<td>-76.088333</td>
<td>36.906667</td>
<td>5</td>
</tr>
<tr>
<td>Norfolk</td>
<td>-76.298889</td>
<td>36.85887</td>
<td>6</td>
</tr>
<tr>
<td>Rescue</td>
<td>-76.562778</td>
<td>36.974722</td>
<td>--</td>
</tr>
<tr>
<td>Gray</td>
<td>-76.805833</td>
<td>37.177222</td>
<td>--</td>
</tr>
</tbody>
</table>

In this section, inundation simulations were conducted using the NAM wind, the WRF-GFS wind, and the RAMS-GFS wind. Simulated coastal flooding was examined at 6 sensor-deployed locations (Figure 4.41), including Messick, Poquoson, Langley, Seaford, Lesner, and Norfolk, by comparing to USGS flooding records. The recorded maximum water elevation at each site, along with the date and time it occurred, are shown in Table 4.7. It can be seen that the maximum water elevation was mostly recorded around 11/13/2009 00:00 GMT, around which time the highest surges were also spotted at NOAA tidal gauge stations near the Bay mouth. At Langley and Norfolk, inundation heights reached more than 2 m during the storm.

Table 4.7 Recorded maximum water elevations at 6 selected locations

<table>
<thead>
<tr>
<th>Sensor Location</th>
<th>Date and Time (GMT)</th>
<th>Water level (m, MSL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Messick</td>
<td>11/12/09 23:42</td>
<td>1.977</td>
</tr>
<tr>
<td>Poquoson</td>
<td>11/12/09 23:00</td>
<td>1.898</td>
</tr>
<tr>
<td>Langley</td>
<td>11/12/09 23:36</td>
<td>2.029</td>
</tr>
<tr>
<td>Seaford</td>
<td>11/12/09 22:30</td>
<td>1.797</td>
</tr>
<tr>
<td>Lesner</td>
<td>11/12/09 22:48</td>
<td>1.898</td>
</tr>
<tr>
<td>Norfolk</td>
<td>11/13/09 00:12</td>
<td>2.071</td>
</tr>
</tbody>
</table>

Figure 4.42 gives the inundation comparison between measured water elevation and predicted water elevation generated by the NAM wind at the selected 6 locations. It can be seen that the overall trend of water level fluctuation was well caught, but the peaks were under-predicted at all
6 stations. Simulated maximum water elevations generated by NAM were shown in Table 4.8. The discrepancies found at Messick, Poquoson, Langley, and Seaford reached more than 0.23 m. As the simulated storm tide yielded from the NAM wind was slightly under-predicted at the Lower Bay stations, this explained why the simulated inundation was under-predicted as well.

<table>
<thead>
<tr>
<th>Sensor Location</th>
<th>NAM (m)</th>
<th>WRF-GFS (m)</th>
<th>RAMS-GFS (m)</th>
<th>Ensemble (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Messick</td>
<td>1.745</td>
<td>2.179</td>
<td>2.066</td>
<td>1.949</td>
</tr>
<tr>
<td>Poquoson</td>
<td>1.723</td>
<td>2.216</td>
<td>2.068</td>
<td>1.932</td>
</tr>
<tr>
<td>Langley</td>
<td>1.811</td>
<td>2.349</td>
<td>2.121</td>
<td>2.047</td>
</tr>
<tr>
<td>Seaford</td>
<td>1.659</td>
<td>2.122</td>
<td>2.039</td>
<td>1.857</td>
</tr>
<tr>
<td>Lesner</td>
<td>1.948</td>
<td>2.184</td>
<td>2.097</td>
<td>2.038</td>
</tr>
<tr>
<td>Norfolk</td>
<td>1.936</td>
<td>2.292</td>
<td>2.264</td>
<td>2.126</td>
</tr>
</tbody>
</table>
Figure 4.41  Locations of 6 water level sensors deployed by USGS for inundation measurements in the Greater Hampton Roads area
Inundation yielded from the WRF-GFS wind was compared to the USGS measurements in Figure 4.43. Different from the previous run, it was found that this model run over-predicted the peak at all 6 locations, with discrepancies ranging from 0.2 m to 0.32 m. Simulated maximum water elevations generated by WRF-GFS wind could be found in Table 4.8 as well. This could be explained by the fact that the storm tides generated by the WRF-GFS wind were significantly over-predicted in the Lower Bay as well. With more water being piled up along the coast by the simulated surge, higher inundation water levels could be expected.

The RAMS-GFS wind had the best performance on inundation predictions, since it was the most reliable wind available in this study. This thought was well justified. Figure 4.44 showed that the simulated inundation yielded from the RAMS-GFS wind had the best match to the flooding records at most locations, with discrepancies generally below 0.2 m. Water level was over-estimated at Seaford, with a discrepancy of 0.24 m.

In order to reduce model uncertainties introduced by different forecast winds, the ensemble average of inundation results was calculated and compared to each individual run, shown in Figure 4.45. It was found that the ensemble average did behave better in catching the surge peak by offsetting the model errors. Although this ensemble approach showed certain merits, it should be used with caution, especially under the circumstance that the quality of its individual members is hard to control. In general, it was well determined that the ELCIRC model has a good ability in handling the wetting-and-drying accurately and robustly. It was also demonstrated that a high-resolution, reliable wind field is necessary for the ELCIRC model to yield better inundation predictions. Last but not least, the ensemble ocean forecast approach showed merits in reducing model uncertainties, but should be used with caution.

An exact inundation map for the lower Chesapeake Bay during the November 2009 Mid-Atlantic Nor’easter would be hard to draw. As a CIPS partner, Noblis (http://noblis.org) has generated preliminary inundation maps based on the ELCIRC model results. However, evaluation of those maps would be difficult due to a lack of spatial flooding measurements. More effort should be made on inundation visualization and evaluation in the future.
Figure 4.42  Predicted water level by NAM wind against USGS inundation records
Figure 4.43  Predicted water level by WRF-GFS wind against USGS inundation records
Figure 4.44  Predicted water level by RAMS-GFS wind against USGS inundation records
Figure 4.45  Ensemble average of predicted water level against USGS inundation records
Chapter 5. Sensitivity tests

This chapter describes the sensitivity tests that were conducted to determine how various sources of variation in the model inputs and model configurations can affect the model final outputs. Specifically, three issues in relation to storm surge and inundation modeling were investigated, including: (1) real time ensemble ocean forecasting, (2) effects of local and remote winds, and (3) influence of continental shelf dynamics on storm surge inside the Chesapeake Bay.

5.1 Real time ensemble forecast

Improved storm surge and inundation forecasts can enable officials to issue more timely and accurate flood warnings and make proper evacuation plans, thus reducing deaths and property damage. With the ensemble weather forecast becoming more and more available nowadays, it is necessary to evoke the ensemble ocean forecast for better prediction of coastal storm surge and inundation during severe storms. Similar to the ensemble weather forecast, the ensemble ocean forecast can be evaluated in terms of an average of the individual forecasts, as well as the degree of agreement between various forecasts within the ensemble system. When the ensemble spread is small, and ensemble members show more agreement, forecasters would perceive more confidence in the ensemble average, and the forecast in general.

As indicated in the previous chapter, three sets of 6-day continuous simulations were conducted, and the ensemble average was calculated to assess the overall predictive skill of the ELCIRC model. It should be noted that the forecast winds being employed were post-processing winds, generated by piecing together the real-time forecasts published every 6 hours. It is a good exercise to use continuous winds in the hindcast. However, in the forecast mode, wind fields can only be used as given. A prototype for the Chesapeake Bay real-time ensemble ocean forecast was built up in this study, and its feasibility was tested through a series of experiments. Forecasts were set up for the period of 11/12/09 00:00 GMT to 11/14/09 00:00 GMT. Every 6 hours there would be 3 new forecasts being initiated by the NAM forecast wind, the WRF-GFS forecast
wind, and the RAMS-GFS forecast wind, and made available at that time. Specifically, forecasts were initiated at 11/12/09 00:00 GMT, 11/12/09 06:00 GMT, 11/12/09 12:00 GMT, 11/12/09 18:00 GMT, 11/13/09 00:00 GMT, 11/13/09 06:00 GMT, 11/13/09 12:00 GMT, and 11/13/09 18:00 GMT, separately. The ensemble forecast results were examined at Lower Bay Station Sewells Point only to give an example.

Figure 5.1 shows the behavior of the ELCIRC model in its forecast mode using the NAM wind. Each line with a unique color represents a forecast run starting at a different time. It was demonstrated that an ocean forecast tended to diverge from the true ocean state, as it extended into the future. Forecasts yielded from the WRF-GFS and the RAMS-GFS winds shown in Figure 5.2 and Figure 5.3 also revealed the same problem. Thus, it is our belief that the ensemble forecast approach should be evoked in the real-time ocean forecast to reduce uncertainty.

![Figure 5.1 Water level forecast using the NAM wind](image1)

![Figure 5.2 Water level forecast using the WRF-GFS wind](image2)
The ensemble forecast results at Sewells Point were also examined at different forecasting time. Figure 5.4 gives the ensemble forecasts starting at 11/12/09 00:00 GMT, with the black line representing the ensemble average. It can be seen that the individual forecasts showed more agreement at the beginning of the forecast. As time went by, the ensemble spreads tended to enlarge. This phenomenon can also be found in ensemble forecasts made at other times at Sewells Point, referring to Figure 5.5 through Figure 5.11. Generally speaking, the ensemble average fell among the ensemble spreads, but not necessarily yielded the best result. However, if enough members are included in the future, it is foreseeable that more confidence will be perceived in the ensemble result.
Figure 5.5  Ensemble forecast starting from 11/12/2009 06:00 GMT

Figure 5.6  Ensemble forecast starting from 11/12/2009 12:00 GMT

Figure 5.7  Ensemble forecast starting from 11/12/2009 18:00 GMT
Figure 5.8   Ensemble forecast starting from 11/13/2009 00:00 GMT

Figure 5.9   Ensemble forecast starting from 11/13/2009 06:00 GMT

Figure 5.10  Ensemble forecast starting from 11/13/2009 12:00 GMT
5.2 Remote and local wind effects

Based on Blain et al. (1994), the size of the model domain is crucial for storm surge modeling in the Gulf of Mexico. The domain size can affect the storm surge prediction inside the Chesapeake Bay as well (Shen and Gong, 2008). Open boundary for a large domain can be specified using harmonic constituents. However, if the domain is too small, specification of its open boundary becomes a problem. Under this circumstance, the open boundary would be impacted by large-scale storm systems like hurricanes and nor’easters, and a tidal boundary condition is no longer suitable. As mentioned in Chapter 2, two versions of the model grid were generated to deal with this problem: 1) a large domain grid covering the western extent of the Atlantic West Coast from Nova Scotia to Florida with relatively coarse resolution, and 2) a high-resolution small domain grid covering the Chesapeake Bay and the land portion of Greater Hampton Roads. The large domain grid was mainly used for simulating storm surge along the western extent of the Atlantic, and for providing time-series water level history to the small domain as its open boundary conditions. The high-resolution small domain grid provides for accurate storm surge and inundation simulations inside the Chesapeake Bay. By coupling the large domain with the small domain, we were able to accurately simulate the water level fluctuations in the Chesapeake Bay during the November 2009 Mid-Atlantic Nor’easter.

The effect of remote and local wind effect on water elevation inside the Chesapeake Bay has been well documented (Wang and Elliott, 1978; Wang, 1979a;b). To further investigate the relative importance of the remote and local wind effects during the November 2009 Mid-Atlantic
Nor’easter, two sets of model simulations were conducted using this coupling approach mentioned above. For Scenario 1, wind forcing was only applied inside the Chesapeake Bay; for Scenario 2, wind forcing was only applied outside the Chesapeake Bay. The base run includes both the local and remote winds. In this study, the RAMS-GFS wind was used in both scenarios.

Figure 5.12   Illustration of remote and local wind effects at CBBT

Figure 5.13 Illustration of remote and local wind effects at Windmill Pt.

Figure 5.14 Illustration of remote and local wind effects at Annapolis
After the large domain runs were finished for both scenarios, two sets of time-series water level data were extracted at the open boundary of the small domain, referred to as Boundary 1 and Boundary 2. Examinations of the two boundaries suggest that Boundary 1 resembles more a tidal boundary, while Boundary 2 incorporates not only the tidal signal but also a surge signal. It becomes obvious that the surge must be induced by the remote wind being applied in Scenario 2. After the small domain runs were finished for both scenarios, simulated water level fluctuations were examined at 11 NOAA tidal gauge stations as well. Figure 5.12 through Figure 5.14 compare the simulated water levels induced by the local and remote winds to the baseline at CBBT, Windmill Pt., and Annapolis. It was well noted that, with the remote wind being eliminated in Scenario 1, the storm surge induced by the local wind was negligible compared to that of the baseline, and a significant set-down was spotted in the Upper Bay region caused by the local wind. In Scenario 2 where the local wind was eliminated, the storm tide induced by the remote wind agreed well with the baseline in the Lower Bay area, and the surge signal propagated from the Bay mouth to the Upper Bay without too much attenuation. If we superimpose the surge generated in Scenario 1 with the surge generated in Scenario 2, as shown in Figure 5.15 through Figure 5.17, the resulting total water elevation is very close to the baseline.

Based on the analysis of model results, it is found that the mechanisms of storm surge are quite different in the lower and the Upper Bay region. In the lower Chesapeake Bay, water level fluctuations are more sensitive to the remote wind than to the local wind. Thus, significant surge near the Bay mouth is mainly caused by the remote wind effect. However, what happens in the Upper Bay is quite different. While the surge signal induced by the remote wind effect propagating from the Lower Bay to the Upper Bay still causes a set-up, a strong local wind effect acts oppositely to produce a major set-down. The total water level fluctuation in the Upper Bay area is affected by the combination of these two effects. As we may recall, storm tide simulation reported in Section 4.3.1 shows that the water level in the Upper Bay region is significantly under-predicted. Sensitivity tests conducted in this section suggested that the large set-down in the Upper Bay could be induced by the local wind effect. Specifically, the surface wind stress in this region is over-estimated during the November 2009 Mid-Atlantic Nor’easter. Thus, the attempt to reduce surface drag coefficient in the Upper Bay area in Section 4.3.2 is further grounded in theory.
Figure 5.15  Comparison of superimposed water level against baseline at CBBT

Figure 5.16  Comparison of superimposed water level against baseline at Windmill Pt.

Figure 5.17  Comparison of superimposed water level against baseline at Annapolis
5.3 Influence of continental shelf dynamics on storm surge inside the Bay

Ekman dynamics (Pond and Pickard, 1998) describe the theoretical state of water circulation for a steady wind blowing over an infinitely deep and wide ocean with constant density, assuming a balance between the friction (wind stress and vertical eddy viscosity) and Coriolis. The analytical solution shows the surface currents at a 45-degree angle to the right of the wind direction in the northern hemisphere, and rotating with depth in a spiral known as the Ekman spiral. The vertical integration of the velocity suggests that the net transport is to the right of the surface wind stress, which is known as the Ekman transport.

The details of the Ekman layer structure depend on several assumptions, which are no longer true in shallow water situation. When translating from theory to practical application in the model, issues of concern are as follows:

(1) The pressure gradient is seldom negligible with the presence of the coast.

(2) The most important assumption, and the one associated with the greatest uncertainty, concerns the process of momentum transfer from the sea surface to greater depths. Transfer of momentum in the ocean is achieved by turbulence. Unlike viscosity, turbulence is not a property of the medium, but of the flow; its intensity and structure depend on the current shear, the stratification, the wave field, the roughness of the ocean floor, and other factors. To describe the effect of turbulent momentum transfer in exact detail requires the knowledge of the details of the eddy field which, under most circumstances, is an impossible task.

(3) The simple relationship between the direction of the wind and the direction of the Ekman layer transport in the deep ocean is valid only when the total water depth is larger than the depth of the Ekman layer. In the shallow water, however, it is not guaranteed that the water depth will always be larger than the Ekman layer. In that case, the Ekman spiral will be significantly modified.

The above issues were addressed in the ELCIRC hydrodynamic model with corresponding strategies. (1) It added the pressure gradient term in the shallow water equation. (2) It included
multiple choices for parameterization of turbulent vertical mixing in the model. Since the surface Ekman layer is a result of wind action, it is also assumed that the wind wave-induced turbulence elements during the storm is important. The particle movement in wind waves is close to an orbital path in a vertical plane. The diameters of the orbital paths decrease exponentially with depth; hence the wind wave-induced turbulence eddy viscosity was included and it decreases exponentially with depth. (3) The realistic topography and shoreline were implemented in the model grid. A benchmark test on simulating Ekman motion in the ELCIRC model can be found at: (http://www.ccalmr.ogi.edu/CORIE/modeling/elcinc/ekman_bench/2.html).

The Ekman transport has been cited as one of the key mechanisms in controlling subtidal water level fluctuation inside the Chesapeake during long periods of wind forcing (Wang and Elliott, 1978). During the November 2009 Mid-Atlantic Nor’easter, a strong and prolonged northeast wind was dominant over the Chesapeake Bay, as well as its adjacent Atlantic West Coast. The contribution of Ekman transport depends on the magnitude of wind forcing, period, and wind directions. We would expect that the westward Ekman transport had a huge impact on the water exchange between the Bay and the continental shelf, and thus on the total water level fluctuations inside the Bay. In this section, the Ekman effect on storm surge prediction inside the Chesapeake Bay during the November 2009 Mid-Atlantic Nor’easter was investigated. Simulations were conducted with and without the Coriolis force being evoked in the model, and model results were examined at CBBT, Windmill Pt., and Annapolis, shown in Figure 5.18 through Figure 5.20. It can be seen that the ELCIRC model results compared favorably with the observations in the lower Chesapeake Bay when the Coriolis force was included, indicating the success of the model in catching the Ekman dynamics. However, when the Coriolis force was not included, the simulated storm tide was notably under-predicted. Sensitivity tests conducted in this section demonstrated that the Ekman transport induced by strong northeast wind has played a major role in pumping water from the continental shelf into the Bay, and as a consequence, causing significant surge and inundation to the coast.
Figure 5.18  Illustration of Ekman effect at CBBT

Figure 5.19  Illustration of Ekman effect at Windmill Pt.

Figure 5.20  Illustration of Ekman effect at Annapolis
Chapter 6. Discussion and conclusion

A prototype for the Chesapeake Bay storm surge and inundation prediction system was developed in this study using the parallel MPI version of ELCIRC model. ELCIRC is an unstructured-grid model, designed for the effective simulation of 3D circulation across river-to-ocean scales. The combination of the Eulerian-Lagrangian scheme with a semi-implicit finite difference method allows it to run over a large domain with ensured stability and computational efficiency. Two sets of model grid were generated for this study: a large domain grid covering the Atlantic Coast from Nova Scotia to Florida, and a high-resolution small domain covering the Chesapeake Bay and the land portion of Greater Hampton Roads. The LiDAR topographic data were incorporated into the high-resolution small domain for the inundation simulation purpose.

The ELCIRC storm surge and inundation simulations in the Chesapeake Bay were conducted for the November 2009 Mid-Atlantic Nor’easter. Forecast winds (the NAM wind, the WRF-GFS wind, and the RAMS-GFS wind) were used to drive the hydrodynamic model. The RAMS-GFS wind was found to be the most reliable wind. Comparisons between simulated and observed water levels at 11 NOAA tidal gauge stations suggested that the quality of storm surge prediction was highly dependent on the quality of forecast winds. Also, the ensemble forecast approach was proved to be beneficial in reducing model uncertainty. The discrepancy of model results found in the Upper Bay area was investigated as well. Further investigations were conducted, using a fetch-limited wind drag coefficient in the upper Bay rather than using the wind drag coefficient suitable for use in the open ocean. As a result, the water level prediction in the Upper Bay was greatly improved. Inundation simulations were also examined over the Greater Hampton Roads area by comparing to USGS measured flooding records. Model results demonstrated that the ELCIRC model has the ability to handle wetting-and-drying with accuracy and robustness.

Sensitivity tests were also conducted in this study to investigate: 1) the feasibility of ELCIRC to conduct real time ensemble forecast; 2) the remote and local wind effects on storm surge predictions; and 3) the influence of continental shelf dynamics on water level fluctuations inside the Bay. It was found that the ELCIRC model was capable of a timely and accurate simulation of
storm surge inside the Bay using multiple real time forecast winds. It was also found that the remote wind effect played an important role in causing the primary surge to the Bay, while the local wind effect was responsible for the major set-down in the Upper Bay. In short, the Ekman transport is one of the key mechanisms in affecting the water level fluctuations inside the Bay during a long period of wind forcing.

The major finding and conclusion of this thesis are summarized as follows:

(1) A high-resolution, unstructured grid hydrodynamic model with an efficient solver was developed and successfully applied for storm surge and inundation simulations in the Chesapeake Bay.

(2) By coupling a large domain grid with a high-resolution small domain grid, the ELCIRC model had a good performance in simulating storm surge in the Chesapeake Bay and the adjacent continental shelf during the November 2009 Nor’easter.

(3) Based on the comparison between ELCIRC model results and NOAA tides/water levels over the entire Chesapeake Bay, the overall RMS is 10 cm, which represents about 5% of error normalized with the maximum surge. The performance of the storm tide prediction depends highly on the quality of weather forecasts. The ensemble forecast approach was proved to be effective in reducing uncertainty by driving the ELCIRC model using NAM, high resolution of WRF-GFS and RAMS-GFS atmospheric modeled wind fields.

(4) It was found that the surface wind drag coefficient was affected by the fetch-limited condition in the Upper Chesapeake Bay. By implementing the revised empirical surface drag coefficient over that area, the prediction in the Upper Bay was greatly improved.

(5) Nine inundation gauge sensors were deployed by the USGS during the November 2009 Nor’easter. The inundation simulation compared exceptionally well with those inundation measurements, which provided confidence for the use of the inundation maps for future operational purposes.
(6) Sensitivity tests were conducted to illustrate the operational real-time forecast, and the important roles played by the remote versus local winds on water level fluctuations inside the Bay. Also, the Ekman transport was proved to be one of the key mechanisms in affecting the surge inside the Bay during a long period of wind forcing.

The prototype of the Chesapeake Bay storm surge and inundation prediction system developed in this study showed great potential and capability to be established as a real time forecast system in the future. However, more investigations still need to be performed. First, although the ELCIRC model has generated satisfying storm surge and inundation simulations for the November 2009 Mid-Atlantic Nor’easter, more test cases should be conducted to validate the capability of the ELCIRC model. Secondly, a wave model should be coupled with the ELCIRC model for better storm surge predictions inside the Bay. Thirdly, with the parallel computing technique being available, ensemble forecast should be further developed for real time forecasting purposes. Last but not least, the wind drag coefficient in the Upper Bay needs to be further investigated for better storm surge prediction.
APPENDICES

Appendix A. Nor’easter intensity scale by Davis and Dolan (1993)

<table>
<thead>
<tr>
<th>Storm Class</th>
<th>Beach Erosion</th>
<th>Dune Erosion</th>
<th>Overwash</th>
<th>Property Damage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Weak)</td>
<td>Minor changes</td>
<td>None</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>2 (Moderate)</td>
<td>Modest; mostly to lower beach</td>
<td>Minor</td>
<td>No</td>
<td>Modest</td>
</tr>
<tr>
<td>3 (Significant)</td>
<td>Erosion extends across beach</td>
<td>Can be significant</td>
<td>No</td>
<td>Loss of many structures at local level</td>
</tr>
<tr>
<td>4 (Severe)</td>
<td>Severe beach erosion and recession</td>
<td>Severe dune erosion or destruction</td>
<td>On low beaches</td>
<td>Loss of structures at community-scale</td>
</tr>
<tr>
<td>5 (Extreme)</td>
<td>Extreme beach erosion</td>
<td>Dunes destroyed over extensive areas</td>
<td>Massive in sheets and channels</td>
<td>Extensive at regional-scale; millions of dollars</td>
</tr>
</tbody>
</table>
Appendix B. Definition of statistical measures for error analysis

The following statistical measures have been calculated to evaluate the quality of forecast winds, as well as the skill of the ELCIRC model in storm surge predictions in this study.

Here, $x$ represents the time series data, and $\bar{x}$ is its time mean, while subscripts “mod” and “obs” denote the model results and observations, respectively.

1. The root-mean-square (RMS) error is defined as:

$$RMS = \left\{ \frac{1}{N} \sum_{i=1}^{N} (x_{\text{mod}} - x_{\text{obs}})^2 \right\}^{1/2}$$

2. The relative error ($E$) is defined as:

$$E = \frac{\sum_{i=1}^{N} (x_{\text{mod}} - x_{\text{obs}})^2}{\sum_{i=1}^{N} ((x_{\text{mod}} - \bar{x}_{\text{obs}})^2 + (x_{\text{obs}} - \bar{x}_{\text{obs}})^2)}$$

3. The correlation coefficient ($r$) is defined as:

$$r = \frac{\sum_{i=1}^{N} (x_{\text{mod}} - \bar{x}_{\text{mod}})(x_{\text{obs}} - \bar{x}_{\text{obs}})}{\left[ \sum_{i=1}^{N} (x_{\text{mod}} - \bar{x}_{\text{mod}})^2 \sum_{i=1}^{N} (x_{\text{obs}} - \bar{x}_{\text{obs}})^2 \right]^{1/2}}$$

4. The model skill is defined according to Warner et al. (2005) as:

$$\text{skill} = 1 - \frac{\sum_{i=1}^{N} |x_{\text{mod}} - x_{\text{obs}}|^2}{\sum_{i=1}^{N} (|x_{\text{mod}} - \bar{x}_{\text{obs}}| + |x_{\text{obs}} - \bar{x}_{\text{obs}}|)^2}$$
LITERATURE CITED


VITA

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