

Toward the Probabilistic Simulation of Storm Surge and Inundation in a Limited-Resource Environment

JUSTIN R. DAVIS AND VLADIMIR A. PARAMYGIN

Department of Civil and Coastal Engineering, University of Florida, Gainesville, Florida

DAVID FORREST

Department of Physical Sciences, Virginia Institute of Marine Science, Gloucester Point, Virginia

Y. PETER SHENG

Department of Civil and Coastal Engineering, University of Florida, Gainesville, Florida

(Manuscript received 7 July 2009, in final form 3 February 2010)

ABSTRACT

To create more useful storm surge and inundation forecast products, probabilistic elements are being incorporated. To achieve the highest levels of confidence in these products, it is essential that as many simulations as possible are performed during the limited amount of time available. This paper develops a framework by which probabilistic storm surge and inundation forecasts within the Curvilinear Hydrodynamics in 3D (CH3D) Storm Surge Modeling System and the Southeastern Universities Research Association Coastal Ocean Observing and Prediction Program's forecasting systems are initiated with specific focus on the application of these methods in a limited-resource environment. Ensemble sets are created by dividing probability density functions (PDFs) of the National Hurricane Center model forecast error into bins, which are then grouped into priority levels (PLs) such that each subsequent level relies on results computed earlier and has an increasing confidence associated with it. The PDFs are then used to develop an ensemble of analytic wind and pressure fields for use by storm surge and inundation models. Using this approach applied with official National Hurricane Center (OFCL) forecast errors, an analysis of Hurricane Charley is performed. After first validating the simulation of storm surge, a series of ensemble simulations are performed representing the forecast errors for the 72-, 48-, 24-, and 12-h forecasts. Analysis of the aggregated products shows that PL4 (27 members) is sufficient to resolve 90% of the inundation within the domain and appears to represent the best balance between accuracy and timeliness of computed products for this case study. A 5-day forecast using the PL4 set is shown to complete in 83 min, while the intermediate PL2 and PL3 products, representing slightly less confidence, complete in 14 and 28 min, respectively.

1. Introduction

Hurricanes are one of the most damaging natural hazards affecting the United States. In 2004, Hurricanes Charley (\$15 billion; U.S. dollars), Ivan (\$14 billion), and Jeanne (\$6.9 billion) made landfall in Florida, causing more than \$35 billion in combined damages (Blake et al. 2007). In 2005, Dennis and Wilma caused additional damages to Florida while Katrina and Rita

caused catastrophic damage in Louisiana and Mississippi. A major contributor to damage caused by hurricanes is associated with storm surge and coastal inundation. These processes not only damage buildings and critical infrastructure but can cause drastic changes in the coastline and the estuarine and coastal ecosystems.

To aid emergency managers in the mitigation and response to hurricane storm surge and inundation, numerous numerical models have been developed. The principles behind these models range from the simple approach of estimating flooding from topographic contours to the more accurate 2D/3D, time-varying, process-based models—such as the Advanced Circulation Model (ADCIRC; Luettich et al. 1992), the

Corresponding author address: Justin Davis, Department of Civil and Coastal Engineering, University of Florida, 365 Weil Hall, P.O. Box 116580, Gainesville, FL 32611-6580.
E-mail: davis@coastal.ufl.edu

Curvilinear Hydrodynamics in 3D Storm Surge Modeling System (CH3D-SSMS; Sheng et al. 2006, 2010), Eulerian–Lagrangian circulation (ELCIRC; Zhang et al. 2004), and Sea, Lake and Overland Surges from Hurricanes (SLOSH; Jelesnianski et al. 1992)—that have been validated for the simulation of storm surge in numerous water bodies around the world. Wave setup can also play an important role in the overall surge height; hence, inclusion of wave physics from a wave model such as Simulating Waves Nearshore (SWAN; Booij et al. 1999) or WAVEWATCH III (Tolman 2002) may also be necessary. In addition, it has been shown that one of the most important factors in the successful simulation of storm surge and inundation is a high-quality wind field. For purposes of forecasting, one of the most accurate dynamical hurricane models is the Geophysical Fluid Dynamics Laboratory (GFDL; Bender et al. 2007) model, as was proved during the active Atlantic hurricane season of 2004, where GFDL was the most accurate model for both track and intensity (Franklin 2005). Thus, the computational resource requirements of the simulation of surge and inundation can range widely from seconds to days or even months depending on the simulation length, domain size and resolution, types of processes included, among others.

Once a model has been developed and sufficiently validated for a particular coastal region, the inundation risk of a coastal region can be communicated to emergency managers in one of two methods. For the first method, a set of hundreds or even thousands of hypothetical or historical storms—for example, using the joint probability method (JPM) or the empirical simulation technique (EST)—can be simulated and then combined to form a surge atlas. This method is convenient in that all computational work can be performed prior to an event, thus greatly increasing the number of possible scenarios simulated. However, because of the wide range of possible storm tracks and intensities, future storm events may not be similar to those in the atlas. In addition, because the set of precomputed storms is necessarily large, it is not possible to present either the temporal characteristics of the systems response or the pathways of flooding.

For the second method, the expected response can be forecasted in real-time, using characteristics of the actual approaching storm. This method allows for the most realistic representation of the storm itself and hence the most realistic response. On-demand forecasting also allows for the temporal characteristics and the pathways of flooding to be more easily communicated. Examples of forecasting systems for storm surge include the Lake Pontchartrain Forecasting System (LPFS; available online at <http://www.cct.lsu.edu/projects/LPFS>), the

National Oceanographic Partnership Program (NOPP) sponsored Real-Time Forecasting System of Winds, Waves and Surge in Tropical Cyclones Project, the Chesapeake Bay Inundation Prediction System (CIPS; available online at <http://cbos.org/Home/chesapeake-bay-inundation-prediction-system-cips>), the North Carolina State University Coastal Marine Environment Prediction System (CMEPS) (Pietrafesa et al. 2002), the National Oceanic and Atmospheric Administration (NOAA) SLOSH Forecasting System (available online at <http://www.nhc.noaa.gov/HAW2/english/surge/slosh.shtml>), and the modeling system tested in this study: the CH3D-SSMS Forecasting System (available online at <http://ch3d-ssms.coastal.ufl.edu>).

To enable more useful interpretation of the response and understanding of forecast uncertainty (Safford et al. 2006), probabilistic elements can be introduced into storm surge forecasting using, for example, atmospheric forcing derived from historical National Hurricane Center (NHC) track guidance error. However, depending on the complexity of the models used, the number of simulations to be performed can be significantly limited because of the timeliness of the approaching storm. In either of the two methods mentioned earlier, various models and scenarios can be implemented and synthesized. However, from the emergency manager's perspective, for a specific storm, a single response product that combines relevant information is desired. During an impending event, there is not enough time, nor do emergency managers necessarily have the required skills, to synthesize the possible different responses of multiple surge and inundation models coupled with multiple atmospheric/wave/or other models. Thus, methods used to determine which models and scenarios are to be performed must be developed in a way such that the resulting system response can be aggregated in a statistically sound manner. The demand for these types of products is evidenced, for example, in how the NHC is now providing a new single probabilistic forecast surge and inundation product (available online at <http://www.weather.gov/mdl/psurge>) created using SLOSH based on a historical analysis of their historical forecast errors.

To achieve the highest levels of confidence in the probabilistic storm surge and inundation forecast products, it is essential that as many simulations are performed as possible during the limited amount time before landfall. Currently, NHC forecast guidance extends out 5 days with errors increasing significantly after 3 days. Since evacuation clearance times (time required to evacuate prior to prelandfall hazards) for densely populated or isolated coastal counties—for example, Miami-Dade (28.4 h) or Monroe County (Key West) (35.8 h), Florida (SFRPC 2006)—may require as much as 1–2 days' public

TABLE 1. Computational resource requirements of some of the models used within SURA SCOOP program.

Model	Processes simulated	Emphasis	Domain	Wall clock time (5-day forecast)
CH3D	Surge/inundation	High-resolution local	Charlotte Harbor, FL	15 min/1 processor
			Tampa Bay, FL	30 min/1 processor
			Northern Gulf of Mexico	1 h/1 processor
			East coast of FL	4.5 h/1 processor
ELCIRC	Surge/inundation	High-resolution local	Chesapeake Bay, VA	30 min/6 processors
			Mid-Atlantic Bight	1 h/6 processors
ADCIRC	Surge /Inundation	Low-resolution regional	Northwest Atlantic Ocean and the Gulf of Mexico	1 h/8 processors
WW3	Waves	Low-resolution regional	Northwest Atlantic Ocean and the Gulf of Mexico	1 h/64 processors

notice for the most effective evacuation orders, a significant amount of computational work must be performed within a very short time frame. Even within the federal government, there are limited resources available to perform these simulations. This issue of how to best balance the need for better probabilistic surge products with limited computational resources is one issue addressed by the Southeastern Universities Research Association Coastal Ocean Observing and Prediction (SURA SCOOP) program (Bogden et al. 2007).

The SURA SCOOP program (available online at <http://scoop.sura.org>) is a multi-institution collaboration to prototype transformational information technology focused on the challenges of predicting coastal hazards. The SCOOP mission is to prototype a distributed network of shared resources that will broaden access to the requisite data, models, computational resources, and other key components of a comprehensive real-time environmental prediction system. Many of the primary data sources and modeling capabilities already exist in the information silos of operational agencies, private enterprise, and research institutions. Data from these systems are increasingly available because of the adoption of community standards from organizations such as the World Wide Web Consortium (W3C; available online at <http://www.w3.org>) and the Open Geospatial Consortium, Inc. (available online at <http://www.opengeospatial.org>). The SCOOP vision is to leverage and integrate the disparate data sources in an information architecture that enables transformational science and provides innovative science products. Examples of some of the surge and wave products used within the SCOOP program are shown in Table 1.

This paper begins to develop the framework by which probabilistic storm surge and inundation forecasts within the CH3D-SSMS Forecasting System, as well as within the larger SCOOP system, are initiated with specific focus on the application of these methods in a limited-resource environment. The specific modeling system and ensemble

methods presented herein represent only one possible instantiation of the framework. Using the basic methodology presented, alternative models and ensemble methods can be employed. An example of this are the other models used within SCOOP (e.g., ELCIRC, ADCIRC, and WW3), which are currently using the ensemble parameters discussed herein. Background on how probabilistic ensembles are created within the SCOOP program is presented in section 2, followed by how these methods are optimized for a limited-resource environment in section 3. Implications for how this priority system affects forecast surge and inundation products for Hurricane Charley is presented in section 4. Related efforts focusing on individual aspects of the forecasting techniques and methods to improve the quality of simulated parameters are briefly described in section 5. Lastly, a summary and conclusions are presented in section 6.

2. Ensemble generation

There are many different methods by which an ensemble of storm surge and inundation can be created, such as ensembles of processes/coefficients, models, and boundary and initial conditions. All of these methods work reasonably well for hindcasting to help learn about the system/processes being studied as well as to determine the optimal use of modeling systems. However, for forecasting, errors in boundary and initial conditions can sufficiently muddle simulated parameters so that discerning meaningful results from some of these methods can be difficult. One of the most important conditions for successful simulation of surge and inundation is a correctly forecasted atmospheric state; hence, this state is typically the ensemble parameter and is the subject of this study.

Ideally, the generation of an ensemble of forecasted atmospheric state would be created by using high-quality, process-based hurricane models and known uncertainties

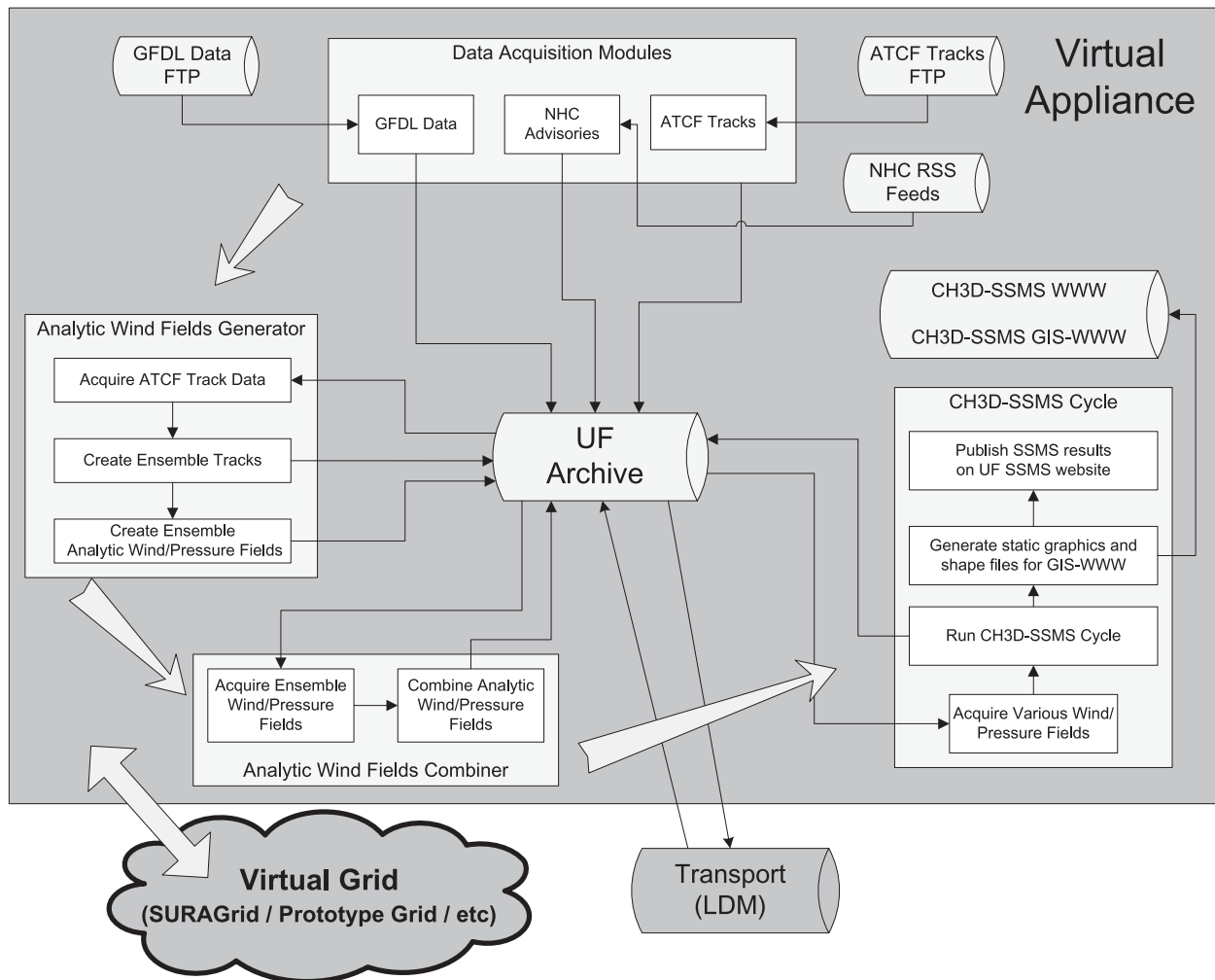


FIG. 1. Work flow for the generation of analytic wind products and operation of CH3D-SSMS within the SURA SCOOP forecasting system.

of the prior state. While the methods presented here will also work for such an approach, at present the computational resources demands of the atmospheric models (hours on multiprocessor systems) coupled with the demands of the surge models make this approach generally impractical for all but a very small ensemble set. Hence, rather than using process-based hurricane models, a simple synthetic/analytic wind and pressure field is used. This method has the advantage of being very computationally efficient (less than a minute on a single processor), thus enabling the creation of large ensemble sets easily. While simplistic in that this method relies only on a few parameters (e.g., position, minimum pressure, radius of maximum wind speed), it is widely used and recognized to work reasonable well (e.g., Hubbert and McInnes 1999; Moon et al. 2003; Madsen and Jakobsen 2004; Peng et al. 2004, 2006; Wolf and Flather 2005; Shen et al. 2006c,b,a; Sheng et al. 2006).

An example of how the generation of the analytic wind and pressure fields fit into the CH3D-SSMS component of the SURA SCOOP program is shown in Fig. 1.

As the primary purpose for creating the ensemble of atmospheric state is for the *forecast* of storm surge and inundation, it is the error of historical forecasted states that is used to generate the ensemble. Forecasted parameters (e.g., position, translational velocity, minimum pressure, and maximum wind speed, as available) are compared with “best track” datasets to determine errors and probabilities that are then used to build an ensemble of forecasted atmospheric state. After which, a corresponding ensemble of storm surge and inundation can be computed. Tropical cyclone model [official National Hurricane Center (OFCL), interpolated official forecast (OFCL), GFDL, Statistical Hurricane Intensity Prediction Scheme (SHIPS), etc.] forecast track and intensity data are obtained from the Automated Tropical Cyclone

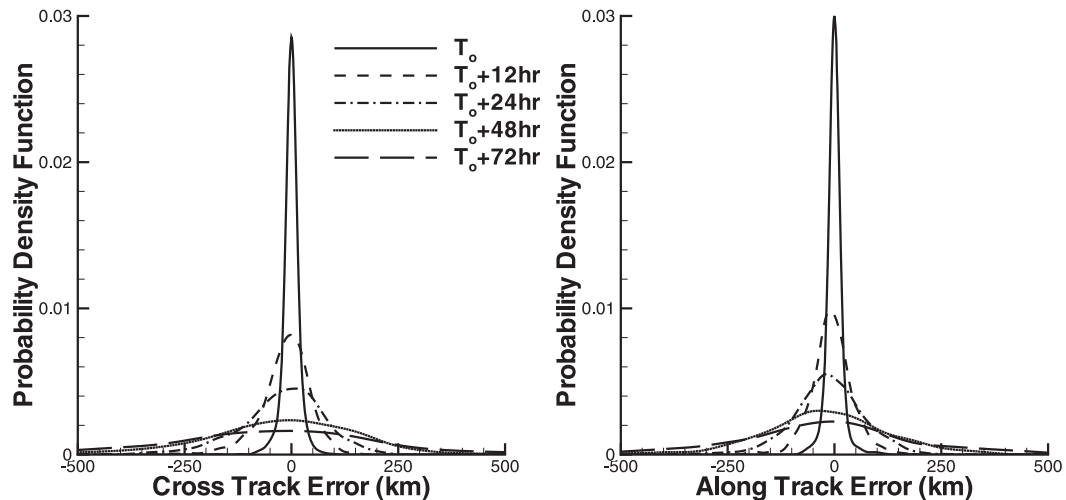


FIG. 2. Empirically derived PDFs for (left) CT and (right) AT error of the NHC's Atlantic OFCL forecast during years 2004–06.

Forecast (ATCF) file/“deck” data. ATCF data have been available to the general public near-real time since the 2003 hurricane season and is updated within six minutes of an active ATCF update (Stewart 2010). The ATCF data published by the NHC are formally used as part of the Automated Tropical Cyclone Forecasting System currently in operation at the Naval Research Laboratory in Monterey, California. This system consists of software designed to automate and optimize the tropical cyclone forecasting process at operational U.S. Department of Defense and National Weather Service tropical cyclone warning centers (Sampson and Schrader 2000). Official historical track and intensity data are obtained from the NHC Atlantic basin hurricane database (HURDAT). The HURDAT is the best-track dataset, containing the “best” track and intensity estimates of tropical cyclones as determined in a postanalysis of all available data for the North Atlantic. Originally developed by Jarvinen et al. (1984), the database is constantly being improved (e.g., Landsea et al. 2004) as well as updated with

information from the latest hurricane season. Data in the HURDAT database include position, minimum pressure, and maximum wind speed—all of which are reported at the same 6-h intervals: 0000, 0600, 1200, and 1800 UTC (coordinated universal time).

Forecast errors for minimum pressure and maximum wind speed are determined by direct comparison of forecasted value and best-track value at a specific forecast hour (e.g., 12, 24, 48, 72 h). As such, this method results in smaller errors for the 12-h forecast and larger errors for the 72-h forecast. Position error is determined in a similar manner, except that the distance and bearing error are calculated and then converted into along-track (AT) and cross-track (CT) errors using the best-track bearing. As positions are recorded in latitude and longitude (a spherical coordinate system), all distance and bearing calculations are performed using “Great Circle”-type calculations. For this study, the PROJ.4 Cartographic Projections Library (available online at <http://trac.osgeo.org/proj/>) was used. To reduce the effects of

TABLE 2. CT and AT errors for the NHC's Atlantic OFCL forecast during years 2004–06, where n is the sample size, μ is the mean, σ is the standard deviation, and JB_{CR} is the critical JB value at the 0.005 significance level. JB exceeds JB_{CR} at all forecast times, thus indicating that neither the CT nor AT errors can be considered normally distributed.

Component	Forecast time (h)	n	μ (km)	σ (km)	Skewness	Kurtosis	JB	JB_{CR}
CT	12	1220	−6.46	49.2	−0.164	5.21	254	12.1
	24	1175	−15.1	83.7	−0.477	5.27	297	12.1
	48	1055	−22.4	150	−0.225	4.02	54.9	12.3
	72	939	−25.0	233	−0.118	5.41	229	12.4
AT	12	1220	−13.6	57.7	−0.862	5.23	405	12.1
	24	1175	−22.7	98.7	−0.710	4.24	174	12.1
	48	1055	−33.8	190	−0.752	4.73	231	12.3
	72	939	−83.8	301	−0.911	5.41	357	12.4

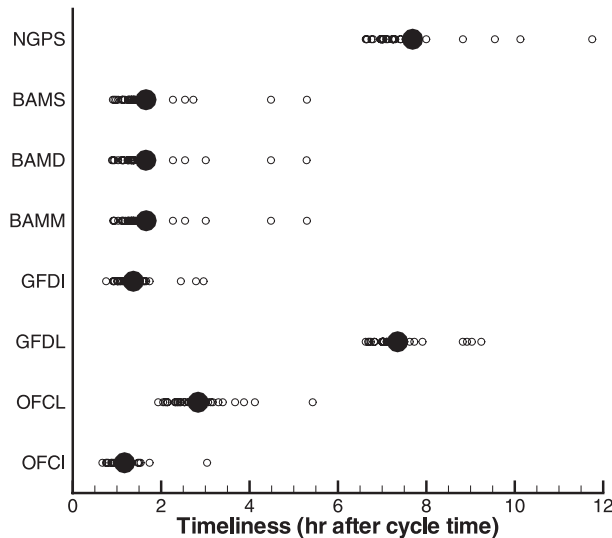


FIG. 3. Timeliness of various hurricane forecast models during the 2005–06 Atlantic hurricane seasons. Mean timeliness for the period is shown with the larger solid circle.

overly active or inactive tropical seasons, multiple years of forecast errors were combined.

Probability density functions (PDFs) for forecast model errors were then developed using kernel density estimation (e.g., Silverman 1986)—also referred to as the Parzen window method (Parzen 1962). A Gaussian kernel was used with $\mu = 0$ and $\sigma^2 = 1$. Bandwidths were selected using Scott (1992) with a factor of 1.06. An example of the PDFs generated for CT and AT errors for the OFCL forecast track during years 2004–06 is shown in Fig. 2. CT and AT were uncorrelated ($r < 0.1$) for all forecast times. Additionally, a Jarque–Bera (JB) test (Bera and Jarque 1980, 1981) was performed on both the CT and AT errors. This test, a goodness-of-fit measure of departure from normality based on the sample kurtosis and skewness, indicated that neither error can be considered normally distributed (Table 2).

With PDFs for CT, AT, minimum pressure, and maximum wind speed errors developed, a probabilistic ensemble set can be created for future forecasted hurricanes. For purposes of the presented method, ensembles will be created only using the CT and AT errors. Furthermore, the CT was used to form a probabilistic “rotation angle,” which is based on a mean translational velocity during the measurement sampling period in which the PDFs were created (e.g., 12.66 kt for the period from 2004 to 2006). The resulting rotation angle PDF is divided into equal-area bins, the center of each then represents rotation angles of equal probability, which when combined with other forecasted parameters (e.g., minimum pressure) yields an ensemble set of forecast tracks. The forecasted tracks are then converted

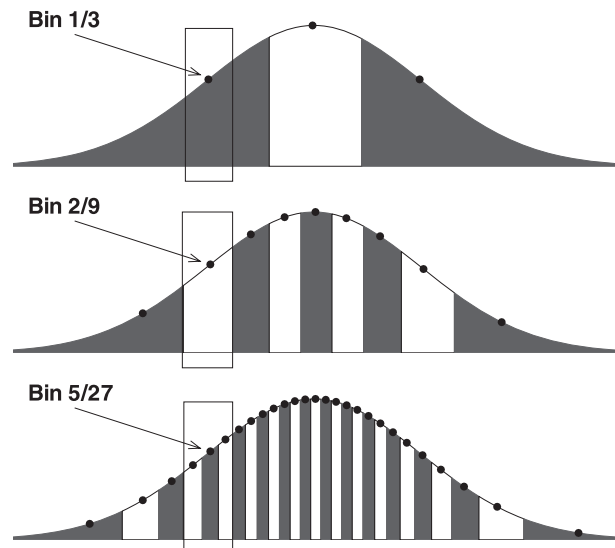


FIG. 4. The division of a Gaussian PDF into 3, 9, and 27 equal-area bins, illustrating how the midpoint of bins $1/3$, $2/9$, and $5/27$ are all located at the same location on the PDF. Bins are numbered consecutively from left to right.

into analytic wind and pressure fields using a simple parametric model (Holland 1980). The wind and pressure fields are then supplied to the storm surge models. As each track represents an equal probability of occurring, the simulated storm surge for each member of the ensemble set can be aggregated into a single forecast product, such as the probability of the water level or flooding exceeding a critical value. This initial methodological framework includes only errors associated with CT and AT forecasts. However, the eventual goal is to use as many forecasts errors as possible, which is currently being done with NHC probabilistic products that use forecast errors associated with hurricane track, wind speed, and an estimate of storm size (DeMaria et al. 2009).

Although the OFCL track is generally the most accurate, the OFCI track is used for forecasting in the SURS SCOOP program because of its timeliness (Fig. 3). Forecasted minimum pressure needed for the analytic formulation (OFCL/OFCI do not contain forecasted pressure) is obtained from the GFDL forecast. As GFDL output is typically not available until six-plus hours after the cycle time, the previous cycle’s minimum pressure is used. Although some accuracy is lost in this approach, the resulting simulated surge is obtained rapidly with analytic wind and pressure fields generated 1–2 h after the cycle time. More accurate analytic fields can be generated using OFCL and the current cycle GFDL, but the fields cannot be generated until 6–8 h after cycle time. Coupled with the simulation time of the

TABLE 3. Description of the 1-, 3-, 9-, 27-, or 81-track ensemble sets for $n = 3$. Members shown in parenthesis have already been computed as part of a previous PL. CL is confidence level and is undefined when there is only one member.

PL	No. of additional members		Members simulated	Total No. of members	Bin area	CL (%)
1-member ensemble						
1	1	1		1	1.000	Undefined
3-member ensemble						
1	1	2		1	1.000	Undefined
2	2	1, (2), 3		3	0.333	66.6
9-member ensemble						
1	1	5		1	1.000	Undefined
2	2	2, (5), 8		3	0.333	66.6
3	6	1, (2), 3, 4, (5), 6, 7, (8), 9		9	0.111	88.9
27-member ensemble						
1	1	14		1	1.000	Undefined
2	2	5, (14), 23		3	0.333	66.6
3	6	2, (5), 8, 11, (14), 17, 20, (23), 26		9	0.111	88.9
4	18	1, (2), 3, 4, (5), 6, 7, (8), 9, 10, (11), 12, 13, (14), 15, 16, (17), 18, 19, (20), 21, 22, (23), 24, 25, (26), 27		27	0.037	96.3
81-member ensemble						
1	1	41		1	1.000	Undefined
2	2	14, (41), 68		3	0.333	66.6
3	6	5, (14), 23, 32, (41), 50, 59, (68), 77		9	0.111	88.9
4	18	2, (5), 8, 11, (14), 17, 20, (23), 26, 29, (32), 35, 38, (41), 44, 47, (50), 53, 56, (59), 62, 65, (68), 71, 74, (77), 80		27	0.037	96.3
5	54	1, (2), 3, 4, (5), 6, 7, (8), 9, 10, (11), 12, 13, (14), 15, 16, (17), 18, 19, (20), 21, 22, (23), 24, 25, (26), 27, 28, (29), 30, 31, (32), 33, 34, (35), 36, 37, (38), 39, 40, (41), 42, 43, (44), 45, 46, (47), 48, 49, (50), 51, 52, (53), 54, 55, (56), 57, 58, (59), 60, 61, (62), 63, 64, (65), 66, 67, (68), 69, 70, (71), 72, 73, (74), 75, 76, (77), 78, 79, (80), 81		81	0.012	98.8

storm surge models, the later approach can result in simulated inundation not being available until after its effective time of usefulness. Another potential issue when combining data from different forecast models (e.g., OFCL track with GFDL minimum pressure) is the inconsistency arising from the different forecasted tracks. For example, the OFCL track may have the storm making landfall later than the GFDL model, in which case the GFDL minimum pressure will be slightly higher (the storm will be less intense) than expected. However, it is expected that the higher amount of uncertainty present within the pressure forecasts themselves currently would overwhelm these potential inconsistencies. In future applications, the NHC maximum wind

forecast could be used as input to a pressure–wind relationship to obtain a more consistent minimum pressure estimate.

3. Prioritization strategies

As mentioned previously, ensemble sets are created by equally dividing PDFs into bins that represent ensemble members that have an equal probability of occurring. In a limited-resource environment, this can be done by simply specifying the number of bins equal to the number of resources available or by selecting some minimum number of simulations to perform for the desired level of confidence in the simulated parameters

TABLE 4. Description of an arbitrary X -member ensemble set for a given priority P , where X is a power of an odd valued n . For the examples presented herein, $n = 3$ and $X = 1, 3, 9, 27$, and 81.

No. of additional members		Members simulated	Total No. of members	Bin area	CL	
1	$(P = 1)$	$(j - 1) \times X/n^{(P-1)} + [X/n^{(P-1)} + 1]/2$	$n^{(P-1)}$	$1/n^{(P-1)}$	Undefined	$(P = 1)$
$n^{(P-1)} - n^{(P-2)}$	$(P > 1)$	where $j = 1, n^{(P-1)}$			$[1 - 1/n^{(P-1)}]$	$(P > 1)$

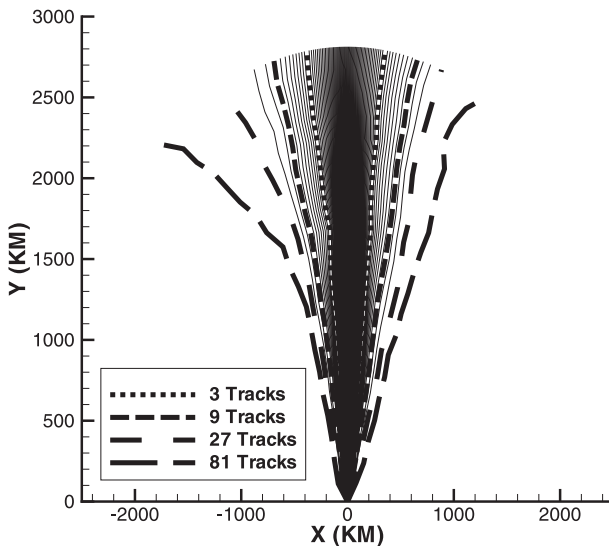


FIG. 5. The 81-track ensemble set based on empirical OFCL forecast error for years 2004–06 for a hypothetical storm starting at (0, 0) and traveling along $x = 0$ at 12.66 kt (the mean translational velocity during this period). Thick lines indicate the farthest counterclockwise- and clockwise-rotated tracks for the 3-, 9-, 27-, and 81-track ensemble sets.

and waiting for all the simulations to complete. Unfortunately, these approaches can be problematic, in that the number of resources may change or resources may have differing performance characteristics that can require the use of complex scheduling algorithms. Additionally, for a large ensemble set, it may take a considerable amount of wall clock time for the simulations to complete with no intermediate products available until then. And if even one simulation fails to complete, then the statistical basis of the aggregated products becomes questionable and no aggregated product at all can be successfully derived. However, through careful division of the PDFs, an ensemble set can be created to avoid these issues.

Rather than dividing the PDFs into an arbitrary number of bins, the PDFs are divided into $X = n^{P-1}$ bins, where X represents the largest ensemble set desired with n being an odd number greater than 1 and P being a “priority level” (PL). For example, for $n = 3$ and $P = 4$, 27 equally spaced bins would be created. As a result of dividing the PDFs in this manner, locations of the midpoint of the bins for P are composed of the midpoints of the bins for $(P - 1)$ plus an additional $n^{(P-1)} - n^{(P-2)}$ locations (Fig. 4). For purposes of performing ensemble simulations, if the individual simulations are performed in a specific order from the PL of 1 to P , then the intermediate simulations can be aggregated to generate a statistically meaningful product. Additionally, as each PL has an associated confidence, as many simulations

can be performed as possible in the limited-resource environment until the desired confidence has been reached or the available wall clock or central processing unit (CPU) times have been exhausted. An example of the simulation ordering of the individual ensemble members for specific cases is shown in Table 3, with a more general case presented in Table 4.

For the simulations presented herein, a PDF of rotation angle is used to generate the ensemble members. An example of the ensemble tracks for an 81-member set for a hypothetical hurricane forecast track is shown in Fig. 5. Each track has a $1/81$ chance of occurring, with many of the tracks concentrated toward the middle where the hurricane has the highest probability of traveling as determined by the empirically derived PDFs for rotation angle.

4. Implications of prioritization on simulated inundation

To understand how the prioritization strategies described herein affect simulated inundation, a set of ensemble tracks was created using one possible example of the generic method discussed in section 2 for Hurricane Charley (2004) and then simulated using CH3D-SSMS. Hurricane Charley made landfall along the southwestern coast of Florida as a category 4 storm (150 mph) (Fig. 6). After first striking Captiva Island, the storm continued along and caused significant wind and flooding damage in Punta Gorda and Port Charlotte. Initially expected to make landfall slightly to the north in Tampa Bay, the storm’s sudden track change caught many in the Charlotte Harbor region of Florida unprepared. As the storm continued on, it blew through Orlando, exited near Daytona Beach, and then made landfall again in South Carolina. All told, the storm was responsible for 10 deaths and caused \$14 billion in property damage, making it the fourth costliest (through the 2006 season) hurricane in U.S. history (Pasch et al. 2007; Blake et al. 2007).

The study area used for simulation is centered on the Charlotte Harbor region (Fig. 7). The domain extends 50–60 km offshore, 105 km alongshore, and inshore to the 5-m topographic contour. With these lateral boundaries defined, a boundary-fitted 141×159 cell grid system was developed (Fig. 8). The minimum cell width is 40 m and, including the offshore region, the average cell width is 700 m. Topography data for the region were obtained from the $1/3$ arc-second (10 m) U.S. Geological Survey (USGS) National Elevation Dataset (NED). Bathymetric data for upper Charlotte Harbor was obtained from the Southwest Florida Water Management District, while data for the remainder of the domain was obtained from the

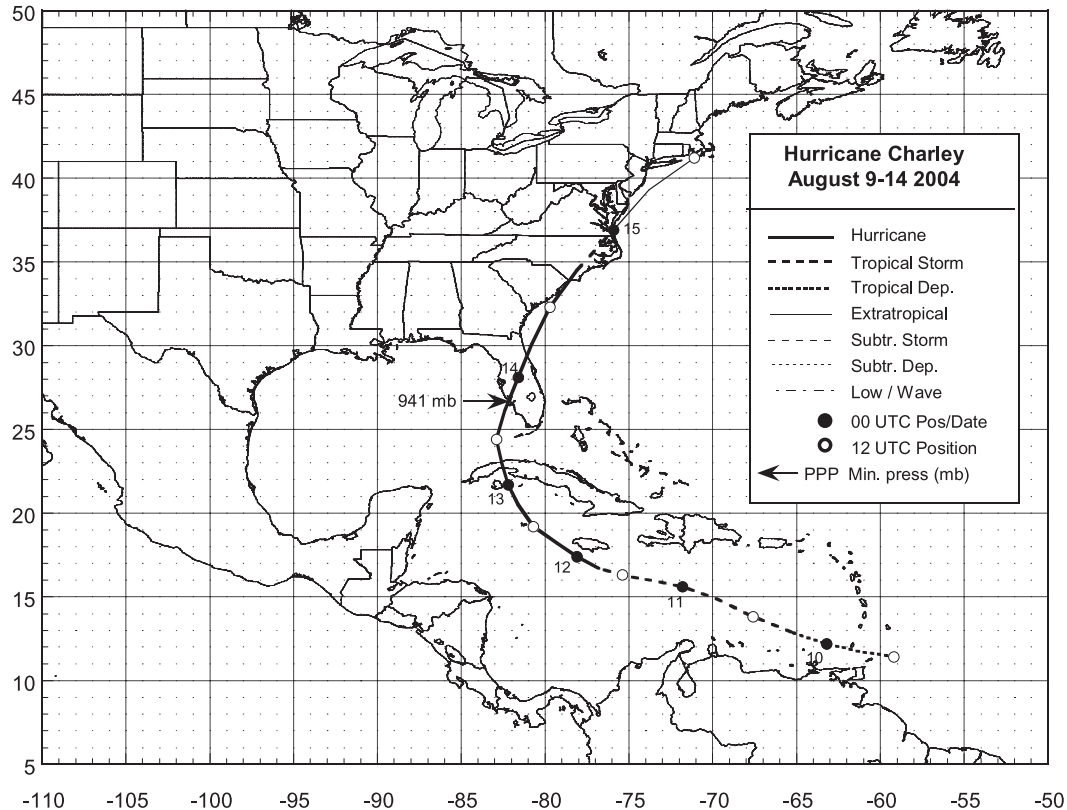


FIG. 6. The track of Hurricane Charley (2004; Pasch et al. 2007). Landfall in Florida occurred on 13 Aug 2004 at 1945 UTC.

National Geophysical Data Center's (NGDC) GEODAS (Geophysical Data System) datasets. Vertically, bathymetry and topography are referenced to the North American Vertical Datum of 1988 (NAVD88). Horizontally, the grid was developed using the High Precision Geodetic Network (HPGN) universal transverse mercator (UTM) coordinate system.

The simulations of storm surge and inundation were performed using CH3D-SSMS, an integrated storm surge modeling system developed at the University of Florida (UF). The modeling system includes the high-resolution coastal surge model CH3D (available online at <http://ch3d.coastal.ufl.edu>), which is coupled to SWAN and large-scale surge [e.g., ADCIRC or Unstructured CH3D (UnCH3D)] and wave (e.g., WAVEWATCH III or SWAN) models. The foundation of CH3D-SSMS is the CH3D model developed by Sheng (1987, 1990). CH3D has been extensively applied to and validated with data from various coastal, estuarine, and lake waters throughout the United States. In addition, CH3D is the cornerstone of the Chesapeake Bay model used by the U.S. Environmental Protection Agency (EPA) and surrounding states to manage the bay's water quality and resources. Since 1986, CH3D has been significantly advanced by UF researchers

and applied to almost all major estuaries and lakes in Florida (e.g., Arnold et al. 2005; Sheng et al. 2008; Sheng and Kim 2009), including Sarasota, Tampa, Florida and Biscayne Bays, Charlotte Harbor, Indian River Lagoon,

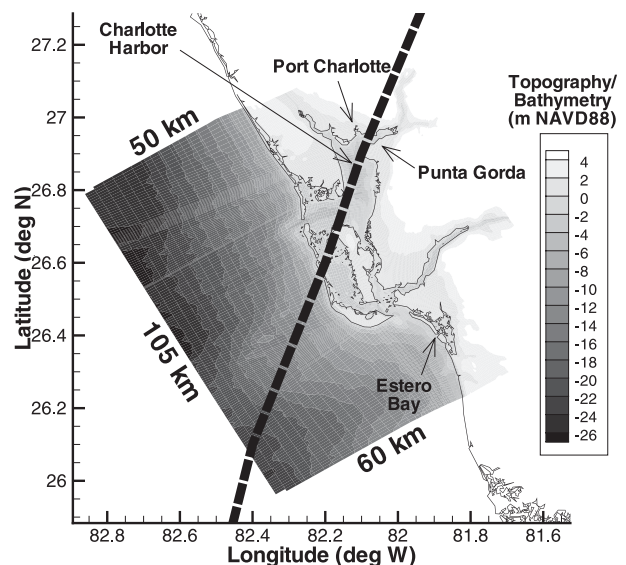


FIG. 7. The Charlotte Harbor study area.

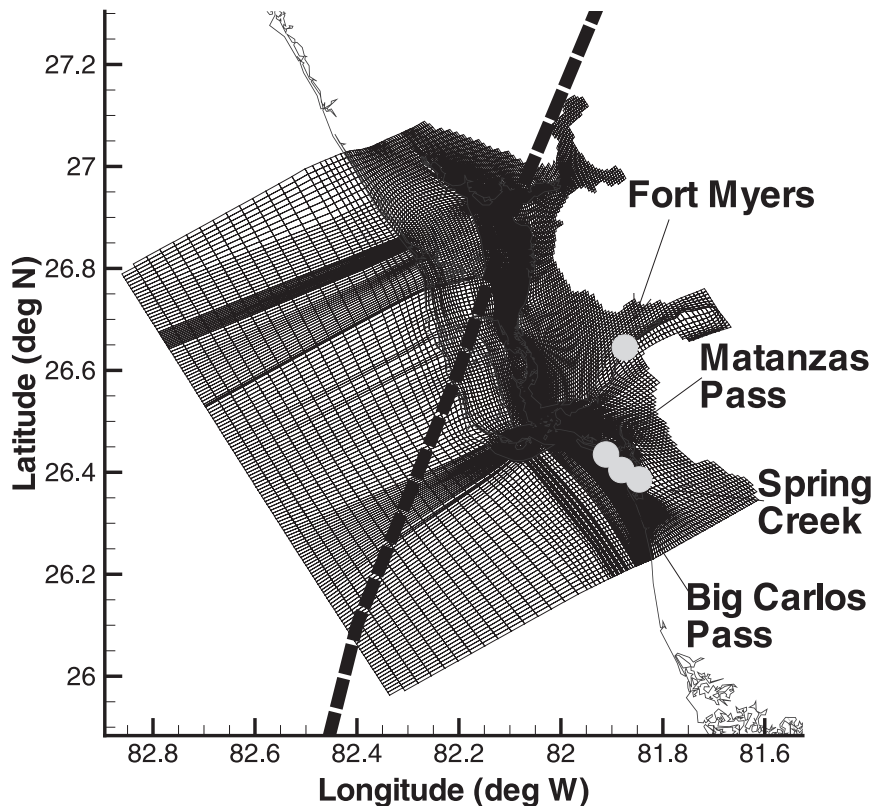


FIG. 8. The boundary-fitted curvilinear grid system (141×159 cells) used for simulation.

and St. Johns River. For simulation of storm surge and coastal inundation, CH3D has been enhanced to include flooding-and-drying; current-wave interaction (current-wave bottom boundary layer, wave-breaking-induced radiation stress, and wave drag); variable bottom roughness, depending on the variable land use types; and the ability to operate with various realistic or analytic wind and pressure fields.

CH3D-SSMS has been used to simulate many of the hurricanes during 2003–05, including Isabel (Sheng et al. 2010), Charley, Frances, Ivan, Dennis, Katrina, and Wilma. Working with Pinellas County and the Federal Emergency Management Agency (FEMA), UF (Sheng and Alymov 2002) used CH3D-SSMS to produce a flood insurance rate map (FIRM) for Pinellas County, Florida, and compare it with the FEMA FIRM. CH3D-SSMS was also used to produce a surge atlas that was compared with the SLOSH surge atlas. Since 2004, CH3D-SSMS has been advanced to provide a real-time forecast of analytic hurricane wind and pressure, storm surge, wave, and coastal inundation for various parts of Florida and Gulf of Mexico coasts during hurricane seasons (Sheng et al. 2006; Davis et al. 2006).

Prior to performing the ensemble simulations, a base simulation is performed to ensure CH3D-SSMS simulates

water levels reasonably well. Using the 2D version of CH3D-SSMS, the base simulation begins at 2000 UTC 10 August 2004, is 4 days in length, and uses a 60-s time step. The simulation is forced by analytic storm wind and pressure fields created by a simple parametric model (Holland 1980) as well as tides. Best-track and pressure data used for creating the storm were obtained from the NHC Tropical Cyclone Report (Pasch et al. 2007). Radius of maximum wind data was estimated from the experimental NOAA Hurricane Research Division (HRD) H*Wind “snapshot” products (Powell et al. 1998). Tidal forcing was achieved using tidal constituents along all open boundaries obtained from the ADCIRC EC2001 tidal database (Mukai et al. 2002). As these constituents are referenced to mean water level (MWL), conversion to NAVD88 was performed by spatially interpolating MWL–NAVD88 differences from available local NOAA benchmark sheets. Lastly, bottom friction for the simulation was calculated using the Manning’s formulation and a spatially constant coefficient of 0.025.

Observed water level available for comparison with the base simulation are available at four sites in the region: Fort Myers (NOAA 8725520), Big Carlos Pass [Coastal

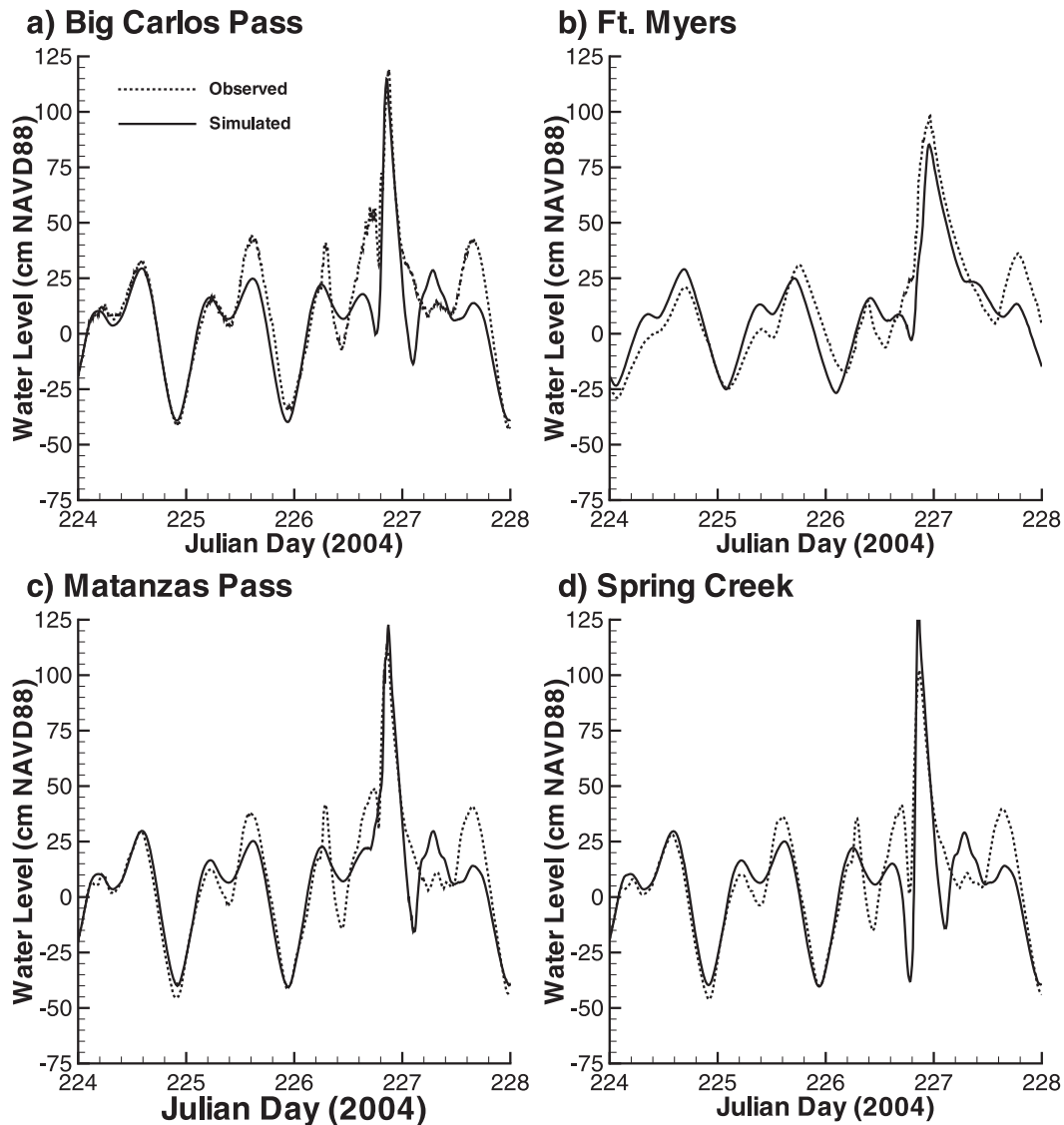


FIG. 9. Comparisons between simulated and observed water level. Peak surge amplitude and phase differences are (a) -4 cm and -35 min, (b) -14 cm and -10 min, (c) 11 cm and 24 min, and (d) 33 cm and -12 min. Positive errors indicate overprediction and phase lag vs observed data.

Ocean Monitoring and Prediction System (COMPS) 1408A552], Matanzas Pass [Florida Department of Environmental Protection (FDEP) EB01], and Spring Creek (FDEP EB02). The Fort Myers observation location is located in the Caloosahatchee River, Big Carlos Pass, at the entrance to Estero Bay, Matanzas Pass, in the northern portion of Estero Bay and Spring Creek in the southern portion.

Comparisons between simulated and observed water level are shown in Fig. 9. Tides and peak surge are reasonably well simulated using the ADCIRC tidal constituents and the analytic wind model as boundary forcing. Big Carlos Pass and Fort Myers slightly

TABLE 5. Overview of the ensemble simulations.

PL	No. of ensemble simulations per forecast length (time before landfall)			
	(i)	(ii)	(iii)	(iv)
	72 h	48 h	24 h	12 h
1	1	1	1	1
2	3	3	3	3
3	9	9	9	9
4	27	27	27	27
5	81	81	81	81
6	243	243	243	243
7	729	729	729	729
8	2187	2187	2187	2187
9	6561	6561	6561	6561

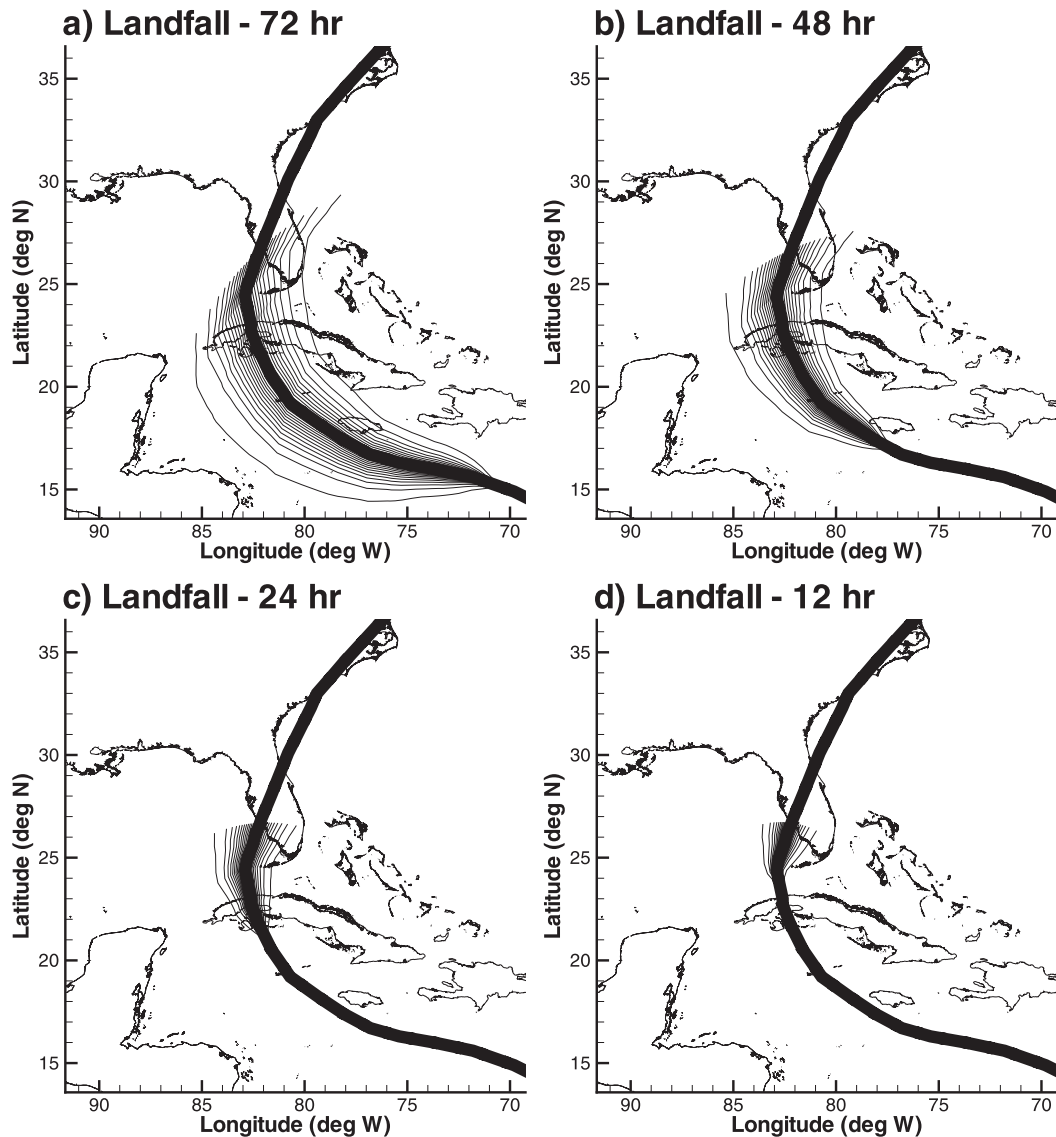


FIG. 10. The PL4 ensemble of forecast tracks for Hurricane Charley (a) 72, (b) 48, (c) 24, and (d) 12 h before landfall. Forecasts extend 24 h past time of landfall. The actual storm track is shown using the solid thick line.

underpredict peak water level. As Big Carlos Pass is the only site exposed directly to the Gulf of Mexico, underprediction may be caused by wave setup effects, which are not included in the simulation. Matanzas Pass and Spring Creek, which are shielded from the Gulf by simulates from barrier islands, overpredict the peaks. This may be due to the poor bathymetric resolution in Estero Bay. Fort Myers is more strongly underpredicted than Big Carlos Pass; however, the phase error is very small even though the peak water level at Fort Myers occurs more than two hours after the other sites. Since this time is long considering the physical scale of the domain, the observed surge may have additional precipitation and discharge components that are not

included in the simulation leading to underprediction. As these base simulation comparisons indicate reasonable simulation of peak surge, it is assumed that the model is reasonably validated for the remaining ensemble analyses, which are all based on maximum of simulation (MOS) and maximum of ensemble (MOE) for water level. A MOS represents the maximum simulated water level at each computational grid point for a single simulation. A MOE represents the maximum simulated water level at each computational grid point over all the MOSs. The MOE-type analysis thus represents the worst-case scenario and is typically what is used by emergency managers for mitigation and planning.

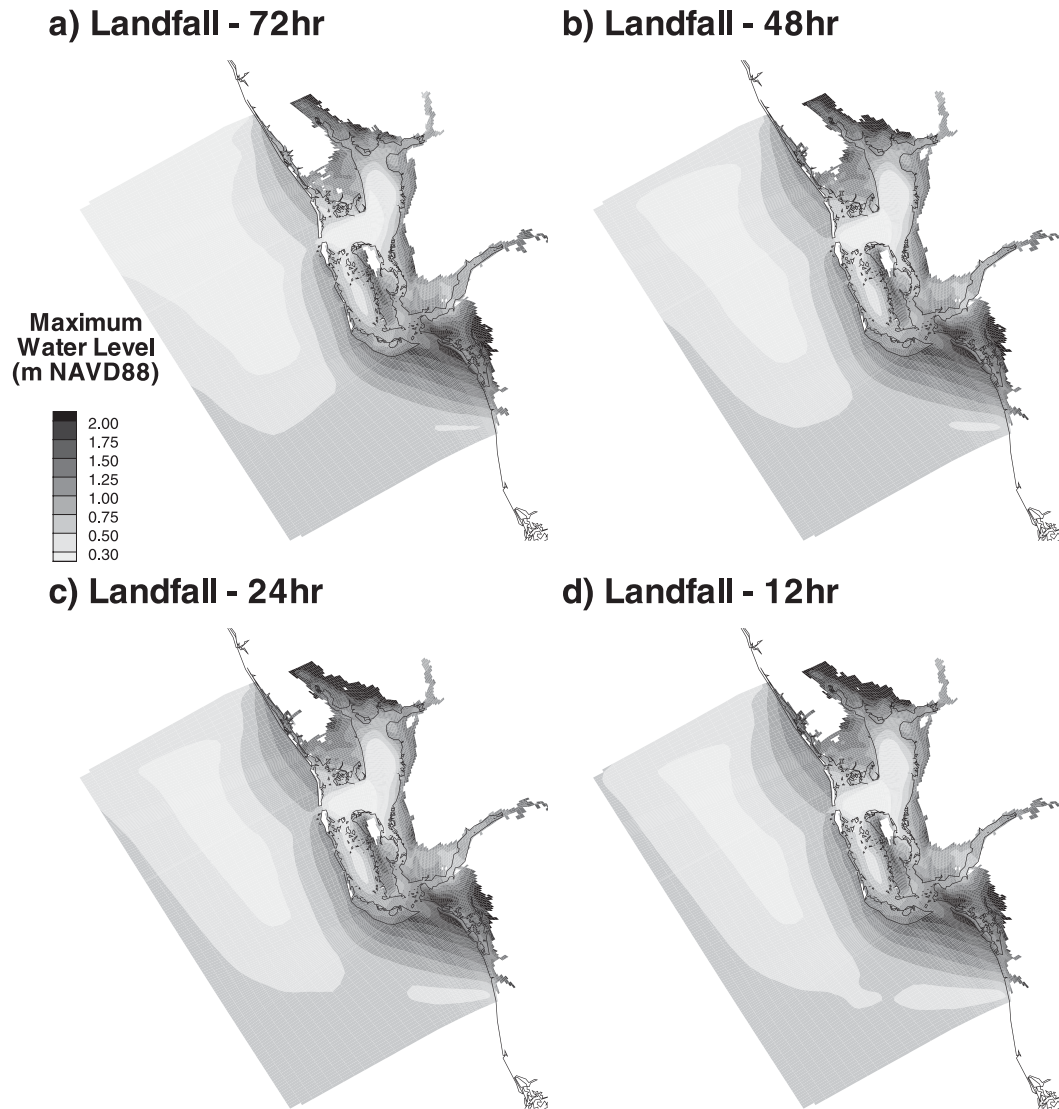


FIG. 11. Simulated water level MOE based on the PL9 ensemble set.

With the base simulation sufficiently validated, the ensemble simulations of storm surge and inundation in Charlotte Harbor are set up and performed. Ensembles are based on the forecast error statistics for the OFCL guidance between 2004 and 2006 and the generic method described in section 2 for creating an ensemble of tracks based on cross-track errors. Using $n = 3$, an ensemble set of storm characteristics was created for each PL from 1 (1 member) to 9 (6561 members) for each of the four forecast periods—(i) 72, (ii) 48, (iii) 24, and (iv) 12 h—before landfall (Table 5). The range of 72–12 h was chosen because the quality of forecast guidance diminishes rapidly for forecasts >72 h, and there is limited usefulness to emergency managers for forecast products <12 h because of the short amount of

time available for wide-scale planning and evacuation. An example of the PL4 ensemble track set is shown in Fig. 10. The remaining hurricane characteristics (translational velocity, pressure drop, etc.) are based on the best-track values used in the base simulation. Forcing mechanisms and simulation parameters used are also identical to the base simulation. It is noted that in a true forecast setting, ensemble perturbations would be applied to forecasted parameters instead of the best track as used in this example application. However, for purposes of demonstrating the ensemble approach, a set of results would be yielded that could not be compared with observed values, thus making their interpretation more difficult. In particular, because the track ensembles are centered on the best track rather than a forecast

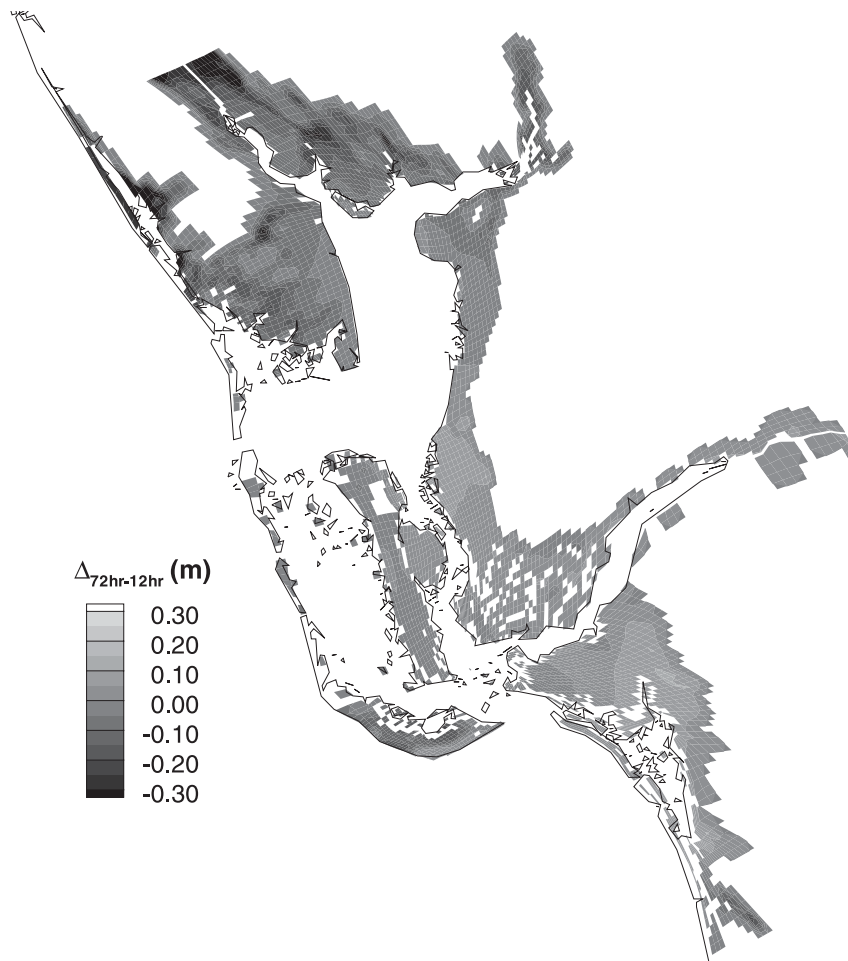


FIG. 12. The difference between the simulated inundation calculated using the 72-h forecast and the 12-h forecast using the PL9 ensemble set.

track as would be necessary in a real-time application, the results presented next on the number of ensemble members needed to capture the true storm surge are illustrative of a case where the track forecast is very accurate. The effect of using track forecasts rather as the baseline is a topic of future research, as will be described in section 5.

With the hurricane characteristics defined for each ensemble member of the four sets of simulations, the entire collection of 26 244 simulations was performed at the UF High Performance Computing Center. Using this resource, a single 4-day simulation required 9.2 min using a single processing element from an AMD dual-core Opteron 275 processor running at 2.2 GHz.

Once completed, the simulated water levels for each of the ensemble sets were aggregated together to generate products useful to emergency managers and to determine the highest PL to use for forecasting. To begin, the water levels for the entire PL9 ensemble set

were combined to form a MOE (Fig. 11). This analysis shows that the peak surge (~ 2 m) is generated outside of the southern entrance to Charlotte Harbor near Estero Bay. This is to be expected, as the counterclockwise rotation of the hurricane piles up water along the south side of the track directly into the funnel-shaped southern entrance to the harbor. Because the ensemble sets were created through variation of the best track, as opposed to forecast track, the variation in the MOE between the 72-h forecast and the 12-h forecast demonstrates the effect of the declining spread of the forecast tracks during this period. Comparing the inundation MOEs between these two forecasts shows that a vast majority of the inundated area is within 0.1 m, thus indicating that if the forecast track of a storm remains constant, then the ensemble spread will not affect simulated inundation significantly in the vicinity of the mean track (Fig. 12).

As the extent and magnitude of inundation are of critical importance to emergency managers, the spatial

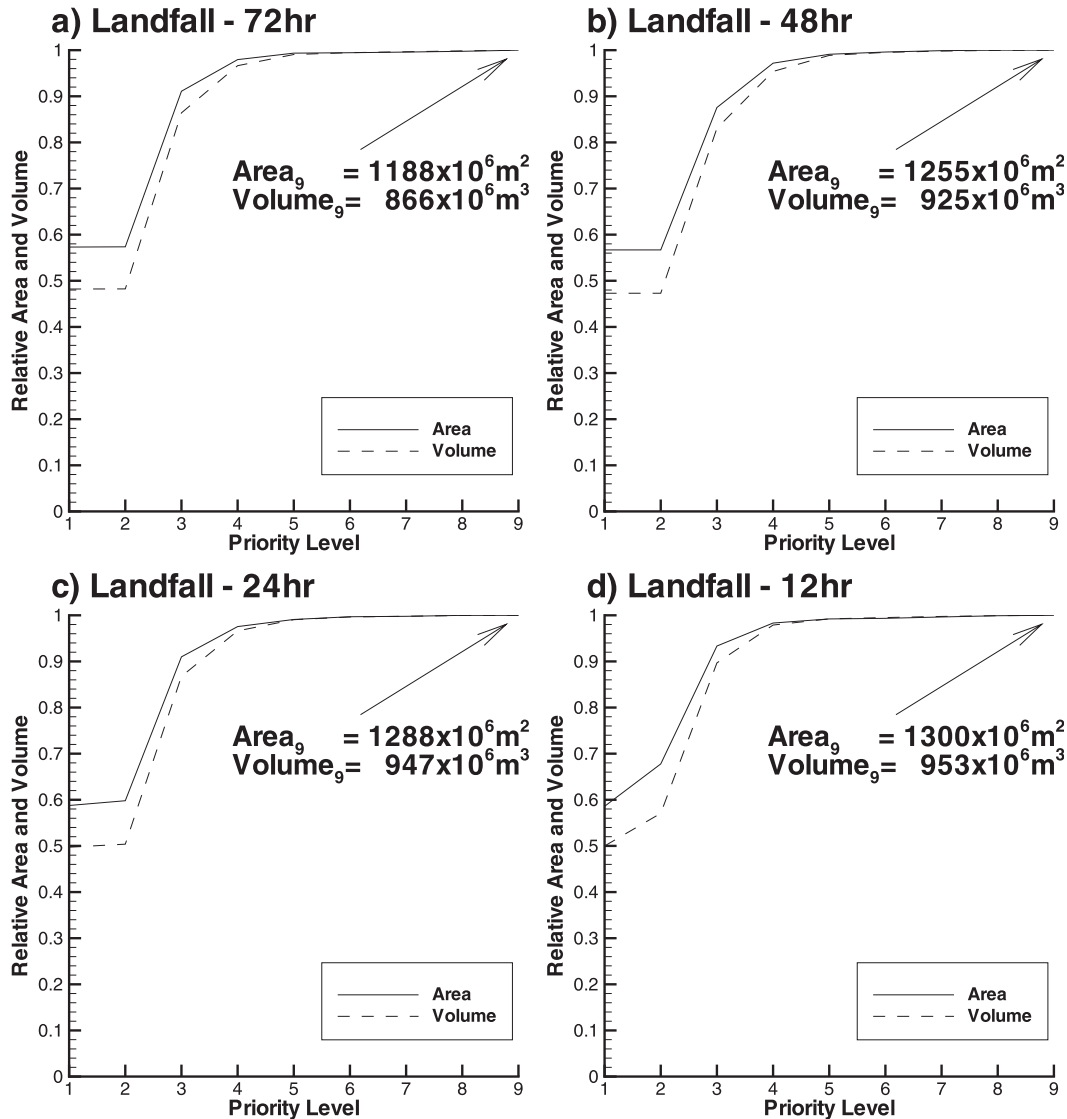


FIG. 13. Relative area and volume of maximum inundation as a function of PL ($n = 3$). Areas and volumes are only calculated in inundated land regions within the domain where the total depth is greater than 1 ft.

areas and volumes of inundated areas within the domain were extracted from water level MOEs for each forecast time and PL (Fig. 13) and then normalized using the PL9 ensemble set. Although inundation occurs over a wide area, the average depth is ~ 0.73 m. Approximately 90% of the inundated area and volume is reached by the time the PL4 set has completed. For PL1, only 45%–60% of the final area and volume is achieved. A slight improvement in these values can be seen when progressing from PL1 to PL2. As expected, this improvement is more pronounced in the 12-h forecast, where more of the ensemble tracks intersect the domain. The largest improvement is seen progressing from the PL2 to PL3, followed by the next largest

improvement between PL3 and PL4. While the inundated areas and volumes continue to approach the reference values, the marginal improvement becomes smaller. These simulated inundation patterns seem to indicate that the PL4 ensemble set would represent a reasonable minimum upper bound to the number of ensemble simulations to perform. This can be further illustrated by comparing the PL4 and PL9 water level MOE; the largest difference is ~ 0.2 m, with a majority of the differences in inundated area amounting to less than 0.1 m (Fig. 14).

Since the ensemble sets were developed using a probabilistic-based approach, it is possible to develop simulated water level “probability of exceedance”

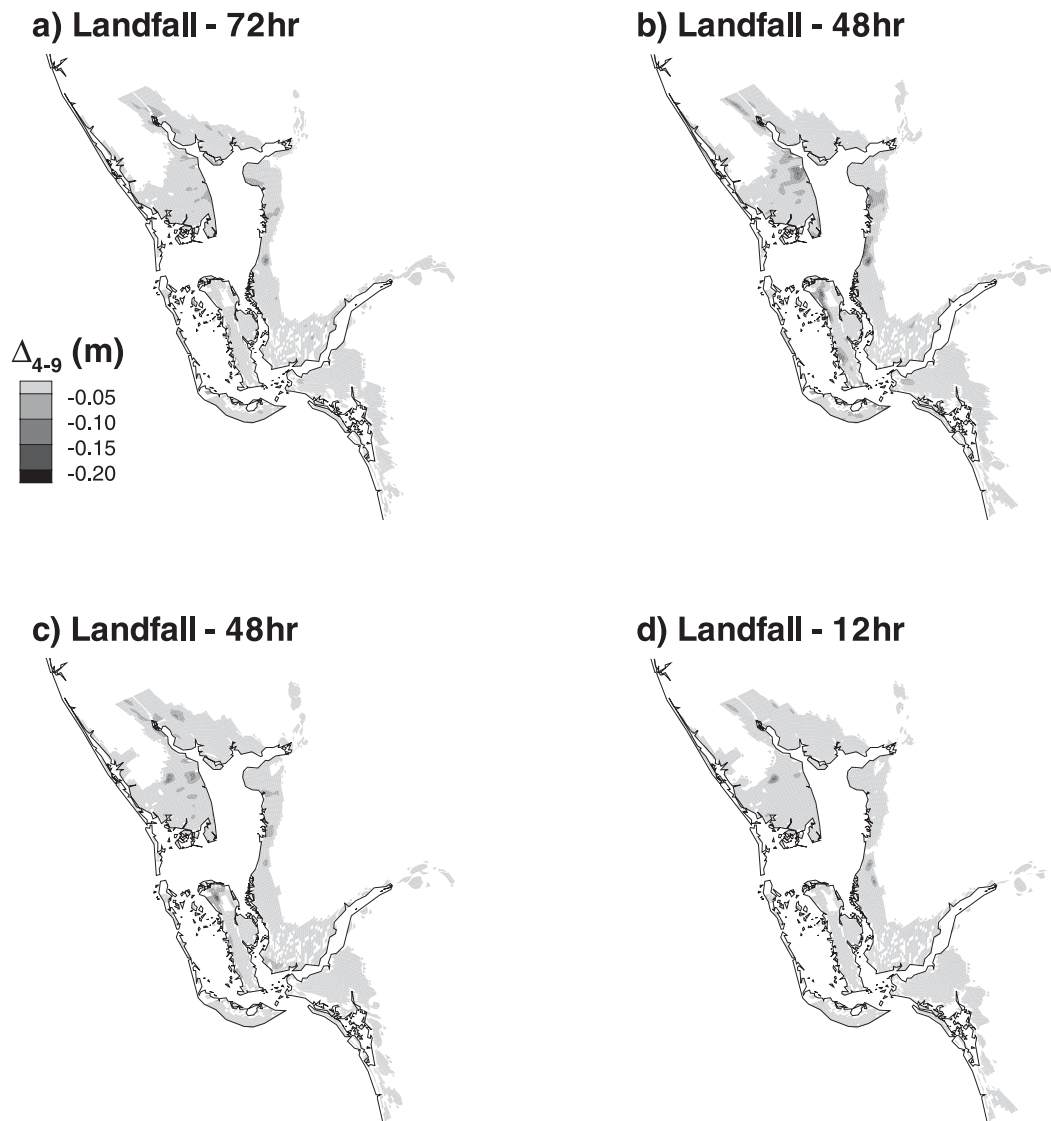


FIG. 14. The difference between the simulated maximum inundation using the PL 4 ensemble set and the PL 9 ensemble set. Negative values indicate the maximum inundation using the PL 9 ensemble set is more extensive than the PL 4 ensemble set.

(POE)-type products. Using the locations of the four observation sites mentioned previously, the POEs were calculated for two cases: 0.5 m (slightly above expected tidal amplitude) and 0.75 m (more significantly above the expected tidal amplitude) NAVD88. For the 0.5-m case, all four sites have a POE = 1 for PL1; however, the probability at each declines with the higher PLs (Fig. 15). Although each site's POE at PL9 is only ~ 0.33 for the 72-h forecast, they do increase to ~ 0.6 for the 12-h forecast, which is another indicator of the effect of the ensemble spread. It is also noted that the POE curve flattens out after PL4. Similar patterns are shown for the 0.75-m case, with the exception that the overall POE

values are lower (Fig. 16). Again, the largest POE increases occur between PL1 and PL3, and the curves flatten off at PL4. Spring Creek has the highest POE, which is somewhat expected, as this location had the highest water level from the base simulation. Again, PL4 appears to be a good minimum upper bound for the number of ensemble simulations to perform.

Looking at the Spring Creek location exclusively, the POE for various water heights relative to NAVD88 can be determined (Fig. 17). For all forecast periods, POE = 1 for 0.25 m. The next highest POE is 0.5 m, which ranges from 0.37 for the 72-h forecast to 0.55 for the 12-h forecast. For water levels at or above 1.5 m, the POE is

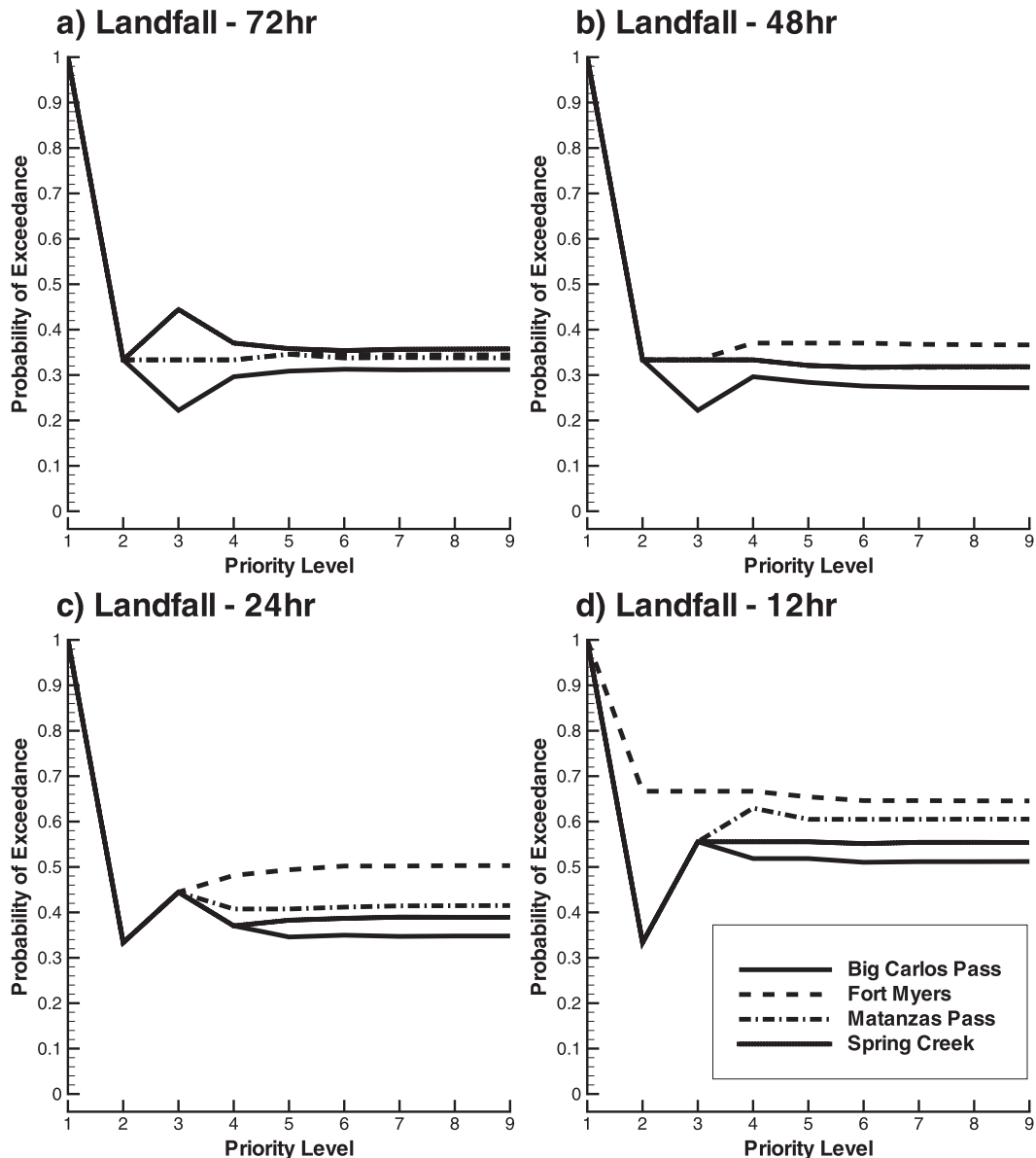


FIG. 15. Probability of the water level MOE exceeding 0.5 m NAVD88.

~0.1, indicating that within the confidence of a given probability level, there was little chance of this high a water level occurring. As with the previous products, the POE curves flatten out after PL4. It is also noted that although the probability of exceeding 0.75 m is relatively low, the base simulation did produce a water level that exceeded this value, thus illustrating a difficulty in interpreting probabilistic results. Rather than focusing on specific POE values, it becomes more useful to look at values that are high relative to other areas. To this end, a product illustrating the spatial extent of the 0.75 m POE is shown in Fig. 18. As with the regions highlighted in ensemble MOE for having high water

levels, the regions with the highest POE 0.75 m occur in the entrance to the southern portion of Charlotte Harbor near Estero Bay and in the upper reaches of Charlotte Harbor itself.

On the basis of the timeliness of the NHC forecast products used to develop the ensembles and subsequently force the surge and inundation models (Fig. 3), it is estimated that forecast surge products need to be completed and ready for use by emergency managers within 3 h of a total 6-h cycle. Factoring in other delays (e.g., data transport and ensemble postprocessing times), it is then assumed that all of the ensemble simulations need to complete within two hours. Extrapolating the

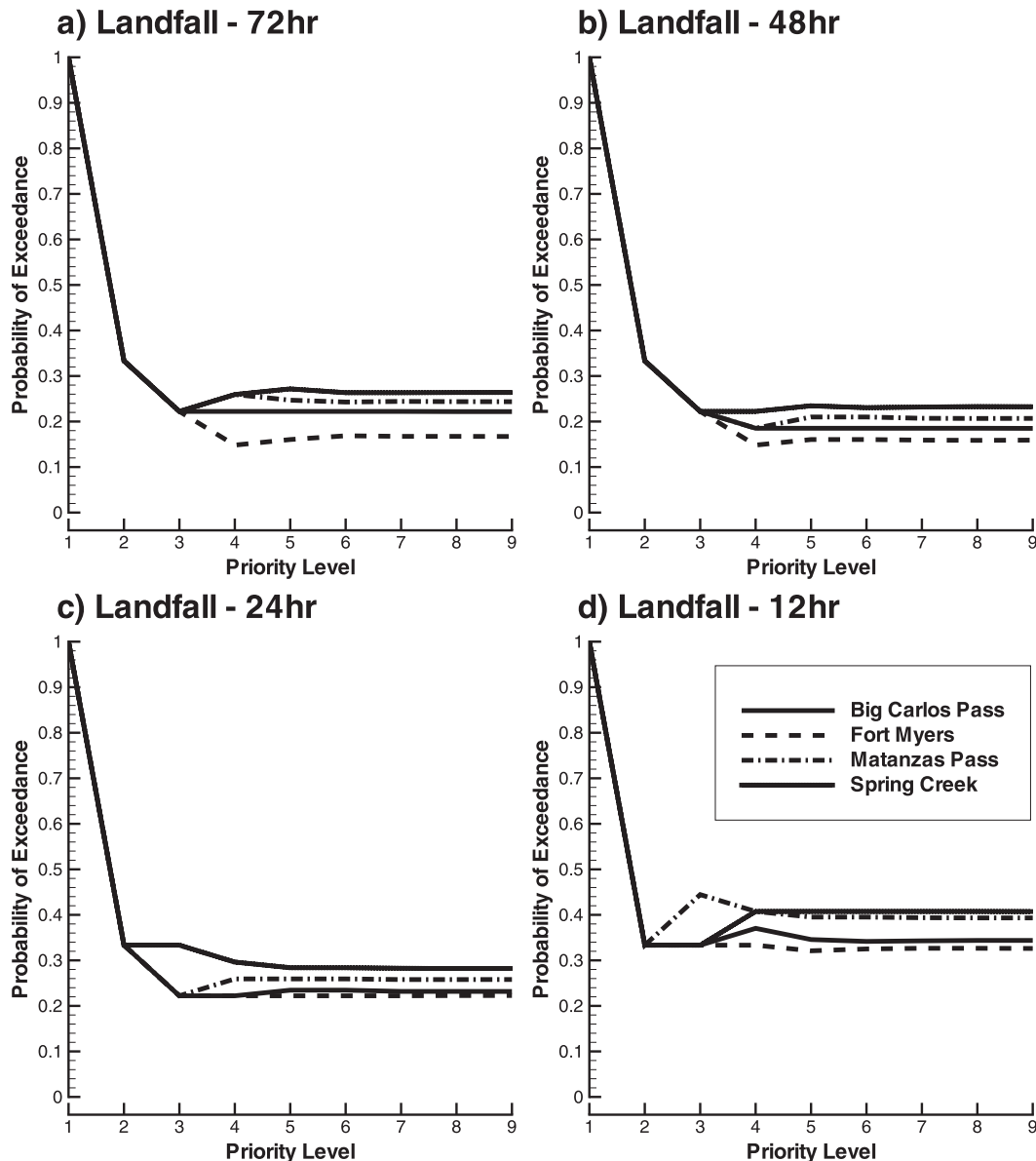


FIG. 16. As in Fig. 15, but for 0.75.

ensemble simulations computation time presented herein to that of a typical forecast (5-day forecast + 1-day model spinup), the simulation time of a single ensemble member T_{EM} is expected to be 14 min [(9.2 min/4-day simulation) $\times$ 6-day simulation]. Assuming the number of ensemble members to complete N_{EM} is 27 (PL4) and the number of processing elements N_{PE} available is 5, it is possible to complete this entire ensemble within only $T_{TOT} = \lceil N_{EM}/N_{PE} \rceil \times T_{EM} = 84$ min. Additionally, assuming the simulations are performed in the specified order (Table 3), the intermediate PL1–PL3 products are available within 14, 14, and 28 min, respectively (Table 6). To optimize the computational resource environment, the

minimum number of processing elements required to compute the ensemble is $(N_{PE})_{min} = \lceil N_{EM}/\lceil T_{TOT}/T_{EM} \rceil \rceil$, where $T_{TOT}/T_{EM} \geq 1$. For PL1, PL2, ..., PL9, $(N_{PE})_{min}$ would be 1, 1, 2, 4, 11, 31, 92, 274, and 821, respectively.

5. Related efforts

The storm surge modeling system, ensemble approaches, forecast implementation techniques, and analysis components used as part of this study will be expanded upon in future publications. Topics to appear include 1) A comparison of the relative importance of track error with intensity error on the simulation of inundation.

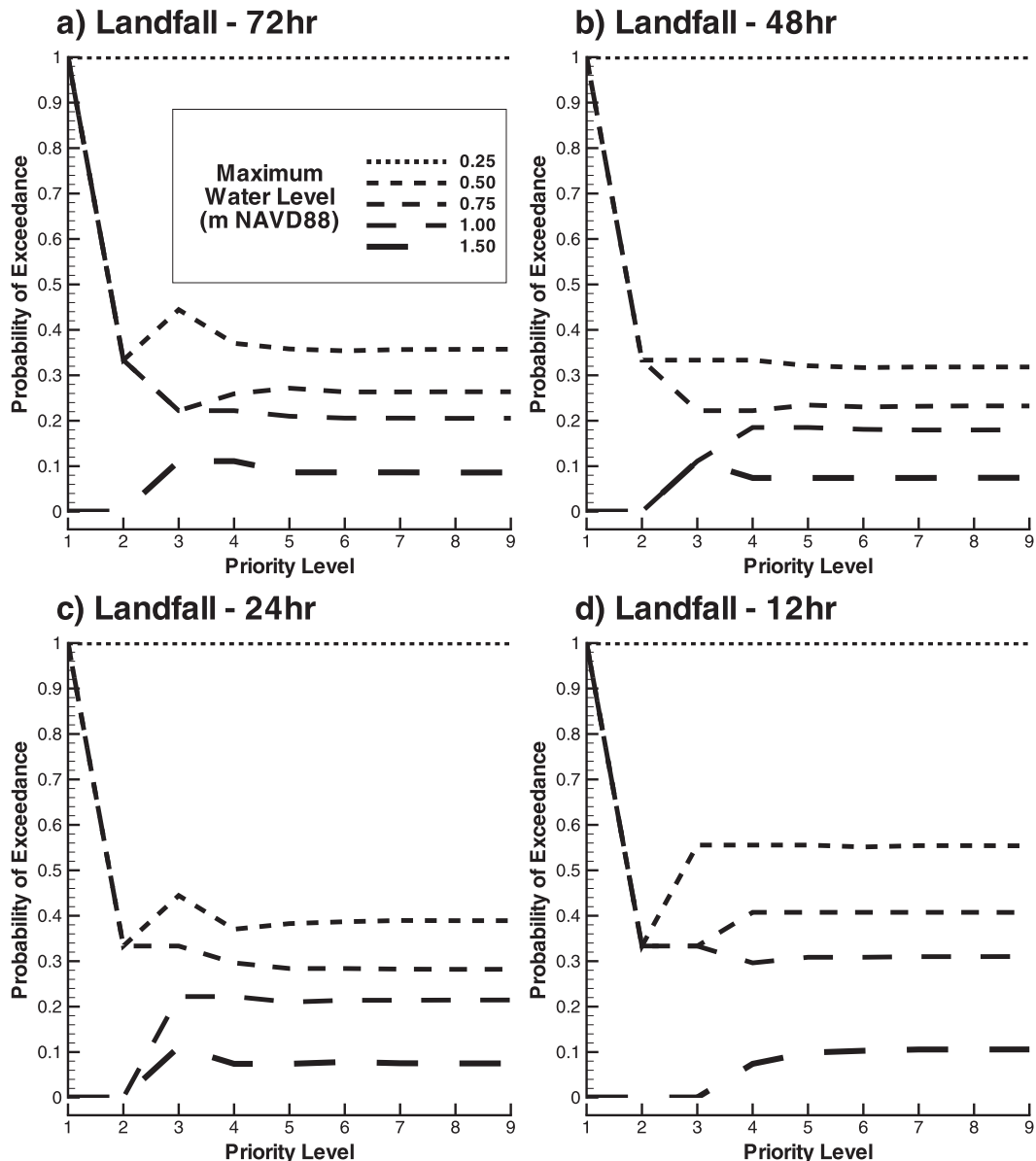


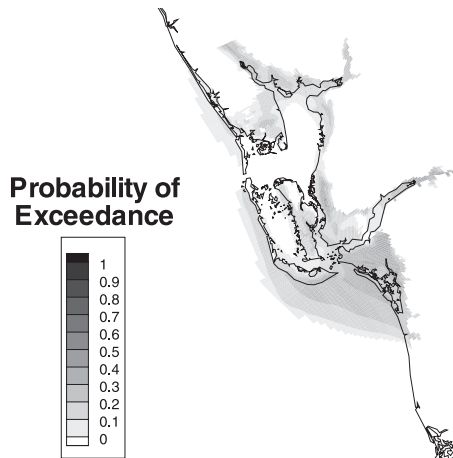
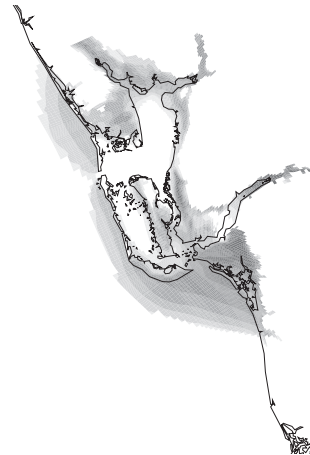
FIG. 17. Probability of water level MOE at Spring Creek exceeding 0.25, 0.50, 0.75, 1, and 1.5 m.

While forecast track error has improved greatly in recent years, intensity error has not. Using forecast error statistics collected of several different results, storm surge simulations are being conducted to investigate how the lack of progress in improving intensity is affecting the forecasted surge in coastal regions. 2) Ensemble simulation of inundation using conditional probabilities. The statistical methods presented herein ignore the paths by which a storm takes. Using conditional probabilities, the path can also be included. This method is currently under investigation. 3) A real-world case study using the prioritization methods described

herein for the SCOOP forecasting will be presented to understand how such algorithms perform during a real hurricane event.

6. Summary

To enable more useful interpretation of the response, probabilistic elements have been introduced into storm surge forecasting using, for example, atmospheric forcing derived from historical NHC track guidance error. To achieve the highest levels of confidence in the probabilistic storm surge and inundation forecast products,

a) Landfall - 72hr**b) Landfall - 48hr****c) Landfall - 24hr****d) Landfall - 12hr****FIG. 18.** The probability of the water level MOE exceeding 0.75 m.

it is essential that as many simulations are performed as possible during the limited amount of time before landfall. This paper has developed a framework by which probabilistic storm surge and inundation forecasts within the CH3D-SSMS Forecasting System as well as within the larger Southeastern Universities Research Association SCOOP system are initiated, with specific focus on the application of these methods in a limited-resource environment. Ensemble sets are created by equally dividing empirically derived PDFs of NHC model forecast error into bins, which represent ensemble members that have an equal probability of occurring. The bins are then grouped into priority levels (PLs), such that each subsequent level relies partially on results computed during an earlier level and has an increasing confidence associated with it. The PDFs are then used to develop an

ensemble of analytic wind and pressure fields for use by storm surge and inundation models. Using this approach applied with OFCL forecast errors, a case study is performed using the landfall of Hurricane Charley (2004) into the Charlotte Harbor region. After first validating the simulation of storm surge using CH3D-SSMS, a series of ensemble simulations are performed representing the 72-, 48-, 24-, and 12-h forecasts.

Analysis of the aggregated products for this case study show that PL4 (27 ensemble members) is sufficient to resolve 90% of the inundation within the domain and appears to represent the best balance between accuracy and timeliness of computed products. Assuming five AMD Opteron 275 2.2-GHz processing elements are available for simulation, it is expected that a 5-day forecast using the PL4 set would take only 83 min to complete,

TABLE 6. Wall clock time (T_{EM}) in minutes required to perform the complete PL1–PL9 ensemble sets. Values are divided into three groups based on their timeliness: $T_{EM} \leq 2$ h (bold), $2 \text{ h} < T_{EM} < 6$ h (normal), and $T_{EM} \geq 6$ h (italic). A single 5-day forecast is estimated to be completed in 14 min.

PL	Number of processing elements								
	1	3	5	10	25	50	100	500	1000
1	14	14	14	14	14	14	14	14	14
2	42	14	14	14	14	14	14	14	14
3	126	42	28	14	14	14	14	14	14
4	378	126	84	42	28	14	14	14	14
5	1134	378	238	126	56	28	14	14	14
6	3402	1134	686	350	140	70	42	14	14
7	10 206	3402	2044	1022	420	210	112	28	14
8	30 618	10 206	6132	3066	1232	616	308	70	42
9	91 854	30 618	18 382	9198	3682	1848	924	196	98

well within the 6-h forecast window of the NHC. The intermediate PL1–PL3 products, representing slightly less confidence, would be available within only 14, 14, and 28 min, respectively.

Acknowledgments. This work was funded by the Southeastern Universities Research Association Coastal Ocean Observing and Prediction (SCOOP) Program funded by the Office of Naval Research, Award N00014-04-1-0721 and by NOAA Ocean Service, Award NA04NOS4730254 and the University of Florida. The authors also wish to acknowledge the University of Florida High-Performance Computing Center (available online at <http://www.hpc.ufl.edu>) for providing computational resources that contributed the results reported within this paper.

REFERENCES

- Arnold, W. S., G. L. Hitchcock, M. E. Frischer, R. Wanninkhof, and Y. P. Sheng, 2005: Dispersal of an introduced larval cohort in a coastal lagoon. *Limnol. Oceanogr.*, **50**, 587–597.
- Bender, M. A., I. Ginis, R. Tuleya, B. Thomas, and T. Marchok, 2007: The operational GFDL coupled hurricane–ocean prediction system and summary of its performance. *Mon. Wea. Rev.*, **135**, 3965–3989.
- Bera, A. K., and C. M. Jarque, 1980: Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Econ. Lett.*, **6**, 255–259.
- , and —, 1981: Efficient tests for normality, homoscedasticity and serial independence of regression residuals: Monte Carlo evidence. *Econ. Lett.*, **7**, 313–318.
- Blake, E. S., E. N. Rappaport, and C. W. Landsea, 2007: The deadliest, costliest, and most intense United States tropical cyclones from 1851 to 2006. NOAA Tech. Memo. NWS TPC-5, 45 pp.
- Bogden, P., and Coauthors, 2007: Architecture of a community infrastructure for predicting and analyzing coastal inundation. *Mar. Technol. Soc. J.*, **41**, 53–61.
- Booij, N., R. C. Ris, and L. H. Holthuijsen, 1999: A third-generation wave model for coastal regions: 1. Model description and validation. *J. Geophys. Res.*, **104** (C4), 7649–7666.
- Davis, J. R., V. A. Paramygin, A. Ganguly, R. J. Figueiredo, and Y. P. Sheng, 2006: Simulation of storm surge using grid computing. *Estuarine and Coastal Modeling 2005*, J. Spaulding, Ed., ASCE, 357–374.
- DeMaria, M., J. A. Knaff, R. Knabb, C. Lauer, C. R. Sampson, and R. T. DeMaria, 2009: A new method for estimating tropical cyclone wind speed probabilities. *Wea. Forecasting*, **24**, 1573–1591.
- Franklin, J. L., 2005: 2004 National Hurricane Center forecast verification report. National Hurricane Center/NOAA Rep., 46 pp. [Available online at http://www.nhc.noaa.gov/verification/pdfs/Verification_2004.pdf.]
- Holland, G. J., 1980: An analytic model of the wind and pressure profiles in hurricanes. *Mon. Wea. Rev.*, **108**, 1212–1218.
- Hubbert, G. D., and K. McInnes, 1999: A storm surge inundation model for coastal planning and impact studies. *J. Coastal Res.*, **15**, 168–185.
- Jarvinen, B. R., C. J. Neumann, and M. A. S. Davis, 1984: A tropical cyclone data tape for the North Atlantic Basin, 1886–1983: Contents, limitations, and uses. NOAA Tech. Memo. NWS NHC 22, 24 pp.
- Jelesnianski, C. P., J. Chen, and W. A. Shaffer, 1992: SLOSH: Sea, lake, and overland surges from hurricanes. NWS Rep. 48, 71 pp.
- Landsea, C. W., and Coauthors, 2004: The Atlantic Hurricane Database Reanalysis Project: Documentation for 1851–1910 alterations and additions to the HURDAT database. *Hurricanes and Typhoons: Past, Present, and Future*, R. J. Murnane and K.-B. Liu, Eds, Columbia University Press, 178–221.
- Luettich, R. A., J. J. Westerink, and N. W. Scheffner, 1992: ADCIRC: An advanced three-dimensional circulation model for shelves, coasts and estuaries, Report 1: Theory and methodology of ADCIRC-2DDI and ADCIRC-3DL. Dredging Research Program Tech. Rep. DRP-92-6, 137 pp.
- Madsen, H., and F. Jakobsen, 2004: Cyclone induced storm surge and flood forecasting in the northern Bay of Bengal. *Coastal Eng.*, **51**, 277–296.
- Moon, I., I. S. Oh, T. Murty, and Y. H. Youn, 2003: Causes of the unusual coastal flooding generated by Typhoon Winnie on the West Coast of Korea. *Nat. Hazards*, **29**, 485–500.
- Mukai, A. Y., J. J. Westerink, R. A. Luettich Jr., and D. Mark, 2002: Eastcoast 2001: A tidal constituent database for western North Atlantic, Gulf of Mexico, and Caribbean Sea. U.S. Army Engineer Research and Development Center, Coastal and Hydraulics Laboratory Tech. Rep. ERDC/CHL TR-02-24, 201 pp.
- Parzen, E., 1962: On the estimation of a probability density function and mode. *Ann. Math. Stat.*, **33**, 1065–1076.
- Pasch, R. J., D. P. Brown, and E. S. Blake, cited 2007: Tropical cyclone report, Hurricane Charley, 9–14 August 2004. [Available online at <http://www.nhc.noaa.gov/2004charley.shtml>.]
- Peng, M., L. Xie, and L. J. Pietrafesa, 2004: A numerical study of storm surge and inundation in the Croatan-Albemarle-Pamlico Estuary System. *Estuarine Coastal Shelf Sci.*, **59**, 121–137.
- , —, and —, 2006: Tropical cyclone induced asymmetry of sea level surge and fall and its presentation in a storm surge model with parametric wind fields. *Ocean Modell.*, **14**, 81–101.
- Pietrafesa, L., L. Xie, and D. Dickey, 2002: NCSU CEMEPS: The North Carolina University Coastal and Estuary Model & Environmental Prediction System. *Solutions to Coastal Disasters '02*, L. Ewing and L. Wallendorf, Eds., ASCE, 441–455.

- Powell, M. D., S. H. Houston, L. R. Amat, and N. Morisseau-Leroy, 1998: The HRD real-time hurricane wind analysis system. *Wind Eng. Ind. Aerodyn.*, **77–78**, 53–64.
- Safford, T., J. Thompson, and P. Scholz, 2006: Storm surge tools and information: A user needs assessment. NOAA Coastal Services Center Rep., 23 pp. [Available online at [http://www.csc.noaa.gov/needsassessments/\(Storm%20Surge\)%20finalstormsurgereport.pdf](http://www.csc.noaa.gov/needsassessments/(Storm%20Surge)%20finalstormsurgereport.pdf).]
- Sampson, C. R., and A. J. Schrader, 2000: The Automated Tropical Cyclone Forecasting System (version 3.2). *Bull. Amer. Meteor. Soc.*, **81**, 1231–1240.
- Scott, D. W., 1992: *Multivariate Density Estimation: Theory, Practice, and Visualization*. Wiley, 317 pp.
- SFRPC, 2006: 2006 South Florida regional hurricane evacuation traffic study. South Florida Regional Planning Council Tech. Support Document, 248 pp. [Available online at <http://www.sfrpc.org/data/RHEMTecSupportFinal.pdf>.]
- Shen, J., K. Zhang, C. Xiao, and W. Gong, 2006a: Improved prediction of storm surge inundation with a high-resolution unstructured grid model. *J. Coastal Res.*, **22**, 1309–1319.
- , H. Wang, M. Sisson, and W. Gong, 2006b: Storm tide simulation in the Chesapeake Bay using an unstructured grid model. *Estuarine Coastal Shelf Sci.*, **68**, 1–16.
- , W. Cong, and H. Wang, 2006c: Water level response to 1999 Hurricane Floyd in the Chesapeake Bay. *Cont. Shelf Res.*, **26**, 2484–2502.
- Sheng, Y. P., 1987: On modeling three-dimensional estuarine and marine hydrodynamics. *Three-Dimensional Models of Marine and Estuarine Dynamics*, J. C. J. Nihoul and B. M. Jamart, Eds., Oceanography Series, Vol. 45, Elsevier, 35–54.
- , 1990: Evolution of a three-dimensional curvilinear-grid hydrodynamic model for estuaries, lakes and coastal waters: CH3D. *Proc. First Int. Conf. on Estuarine and Coastal Modeling*, Newport, RI, ASCE, 40–49.
- , and V. Alymov, 2002: Coastal flooding analysis of Pinellas County using ALSM data: A comparison between UF's 2-D method and results vs. FEMA's method and results. Department of Civil and Coastal Engineering, University of Florida Rep., 67 pp.
- , and T. Kim, 2009: Skill assessment of an integrated modeling system for shallow coastal and estuarine ecosystems. *J. Mar. Syst.*, **76**, 212–243.
- , V. A. Paramygin, V. Alymov, and J. R. Davis, 2006: A real-time forecasting system for hurricane induced storm surge and coastal flooding. *Estuarine and Coastal Modeling 2005*, M. Spaulding, Ed., ASCE, 585–602.
- , B. Tutak, J. R. Davis, and V. Paramygin, 2008: Circulation and flushing in the lagoonal system of the Guana Tolomato Matanzas National Estuarine Research Reserve (GTMNERR), Florida. *J. Coastal Res.*, **55**, 9–25.
- , V. A. Alymov, and V. A. Paramygin, 2010: Simulation of storm surge, wave, currents, and inundation in the Outer Banks and Chesapeake Bay during Hurricane Isabel in 2003: The importance of waves. *J. Geophys. Res.*, **115**, C04008, doi:10.1029/2009JC005402.
- Silverman, B. W., 1986: *Density Estimation for Statistics and Data Analysis*. *Monogr. Stat. Appl. Probab.*, Vol. 26, Chapman and Hall, 175 pp.
- Stewart, S., cited 2010: National Hurricane Center data availability. [Available online at <http://www.aoml.noaa.gov/hrd/hurrdatasession/NHC.pdf>.]
- Tolman, H. L., 2002: User manual and system documentation of WAVEWATCH-III version 2.22. NOAA/NWS/NCEP/MMAB Tech. Note 222, 133 pp.
- Wolf, J., and R. A. Flather, 2005: Modelling waves and surges during the 1953 storm. *Philos. Trans. Roy. Soc. London*, **A363**, 1359–1375.
- Zhang, Y., A. M. Baptista, and E. P. Myers, 2004: A cross-scale model for 3D baroclinic circulation in estuary–plume–shelf systems: I. Formulation and skill assessment. *Cont. Shelf Res.*, **24**, 2187–2214.