Evaluation of a Wind-Wave System for Ensemble Tropical Cyclone Wave Forecasting. Part II: Waves

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ABSTRACT

A wind-wave forecast system, designed with the intention of generating unbiased ensemble wave forecasts for extreme wind events, is assessed. Wave hindcasts for 12 tropical cyclones (TCs) are forced using a wind analysis produced from a combination of the North American Regional Reanalysis (NARR) and a parametric wind model. The default drag parameterization is replaced by one that is more in line with recent studies where a cap at weak-to-moderate wind speeds is applied. Quadrant-based significant wave height ($H_s$) statistics are composited in a storm-relative reference frame and stratified by the radius of maximum wind, storm speed, and storm intensity. Improvements in $H_s$ are gleaned from both downscaling the NARR winds and tuning the wave model. However, the paradigm whereby the drag coefficient depends solely on the wind speed is limiting. Results indicate that $H_s$ is biased low in the right quadrants (for all statistical subcategories). Conversely, $H_s$ is high biased in the left-rear quadrant even though the analysis wind field is underforecast there. At radii less than 100 nautical miles, the model peak wave direction is offset from the observed, with the model (buoy) peak more in line with (to the left of) the direction of the tropical cyclone motion. As a result, the predominant storm-relative wind direction, which is northwesterly in the left-rear quadrant, opposes that of the buoy peak wave direction, while the model peak is more crosswise with respect to the wind. This will likely reduce the magnitude of the wind stress in the model.

1. Introduction

Previous studies have investigated the impact of extreme wind events on wave modeling (e.g., Jensen et al. 2006; Xu et al. 2006; Tolman et al. 2005; Cox et al. 2005). These events are important to a wide ranging set of commercial, recreational, and ocean engineering interests. As such, accurate modeling of the air–sea interface within a tropical cyclone (TC) environment is critical to not only the specification of the sea state but also the evolution of the TC itself through feedbacks that involve the upper ocean (sea spray, momentum and heat fluxes, wind–wave–current interaction, etc.). Even in the most advanced wave models (i.e., third generation or 3G), parameterizations of the physical processes responsible for wave growth are empirically tuned to be accurate under relatively moderate wind conditions (e.g., Chao et al. 2005). When these models are forced with extreme winds, like those associated with a strong TC, wave growth tends to be overestimated due to spuriously large wind stress in the wave growth parameterization (Tolman et al. 2005). Conversely, large-scale atmospheric models tend to poorly resolve TC winds (e.g., Bengtsson et al. 2007). This combination can lead to compensating errors, producing wave heights close to those observed despite being forced with wind fields that underestimate the true TC intensity. This type of behavior in models is well known and not limited to wave growth issues, as it is problematic with parameterizations in general. Parameterizations, which are common components of operational models, require varying degrees of “tuning,” a process in which the model’s free parameters are “fit” to observations in a bulk sense. As a result, parameterizations tend to represent the statistics of typical conditions rather than the extremes. Furthermore, tuning can produce good results, even with seemingly unrepresentative parameters. As a result, an upgrade to a physically more realistic parameterization may not necessarily improve (and may actually degrade) a highly tuned model (e.g., Cavaleri 2009). Regardless of these and other issues,
it is reasonable to expect that a wave model should be driven with an accurate wind field.

In Lazarus et al. (2013, hereafter Part I), the focus was on the evaluation of the TC wind analyses created from a combination of National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) North American Regional Reanalysis (NARR: Kalnay et al. 1996) winds and synthetic observations from a simple parametric wind model. In this second part of this paper, we focus on evaluating and tuning a 2G wave model, the Wave Information Studies (WIS) Wave Model (WISWAVE), forced using these winds. The goal is to minimize bias in the hindcast significant wave heights such that WISWAVE can be used to generate reliable ensemble wave forecasts. WISWAVE, which is described in section 2b, was chosen because it has been shown to compare favorably with 3G models (e.g., Tracy and Cialone 2003) and is computationally efficient, the latter of which is essential for operational ensemble wave simulations. To gauge wave model performance, a hindcast approach is adopted. Albeit ideal, very high-resolution atmospheric models can be an expensive way to generate surface wind fields. A more cost-effective approach to TC wave forecasting, and the approach taken here, is to combine the output from a simple parametric-derived wind field with background (i.e., first guess) winds from an NWP model (e.g., Desjardins et al. 2004; Mousavi et al. 2009). The parametric approach, based on a modified asymmetric Rankine vortex (Knaff et al. 2007), is used to replace the inner-core wind field of a coarse-resolution model (i.e., the NARR) that tends to poorly resolve the TC wind structure and intensity. A total of 12 Gulf of Mexico (GOM) TC events of varying intensities are examined. Wave model performance is evaluated using GOM buoy data from the National Data Buoy Center (NDBC). Using the analysis wind fields generated in Part I to force WISWAVE, the directional resolution and the drag coefficient parameterization are modified in order to improve/tune the wave model. WISWAVE is then run for the 12 TC events (Tables 3 and 4 in Part I) to evaluate its overall performance. Wave model output is stratified in a storm-relative reference frame as well as by radial distance from storm center, storm intensity, translation speed, and size. Results are discussed primarily within the context of minimizing the bias in significant wave height.

2. Data and model

The extended best-track data provided by the National Environmental Satellite, Data, and Information Service (NESDIS) Center for Satellite Applications and Research (Demuth et al. 2006), NDBC buoy observations, and NARR are each described in Part I. The wave model, its domain, and configuration are briefly discussed here.

a. Bottom topography

The topographic data were acquired from the National Geophysical Data Center (NGDC) using the Geophysical Data System (GEODAS) Grid Translator (Design-a-Grid). ETOPO1 (Amante and Eakins 2009), a 1 arc-minute global relief model of the earth’s surface that integrates land topography and ocean bathymetry, is used to construct the WISWAVE domain. The high-resolution topography was mapped to the 10-km WISWAVE grid via bilinear interpolation. A land–water mask is generated directly from this dataset.

b. WISWAVE

The wave model used in this study, WISWAVE, is a discrete 2G spectral wave model that was developed by Resio and Vincent (1977) for the U.S. Army Corps of Engineers (USACE). WISWAVE has been used extensively in wave hindcasting by the USACE offices and throughout the engineering community (Tracy and Cialone 2003, hereafter TC03). For example, using wave data from NDBC buoys in the GOM, TC03 compared the 2G WISWAVE model with the more advanced–complex 3G Wave Action Model (WAM; WAMDI Group 1988; Komen et al. 1994) and WAVEWATCH III (Tolman 1997, 1999a, 2009) models. Their results suggest that the performance of WISWAVE was comparable to the more complex 3G models. Each of the three models, which were shown to have both strengths and weaknesses, proved to be good hindcasting tools and produced results that compared well with measurements (TC03). Furthermore, results from a study performed by Cardone et al. (2000) showed that, in some cases, well-tuned 2G wave models may actually outperform the more advanced 3G models.

WISWAVE solves the time-dependent wave action balance equation:

$$\frac{\partial E(f, \theta)}{\partial t} + C_g(f) \cdot \nabla E(f, \theta) = \sum_{i=1}^{n} S_i$$

(1)

where $E$ is the energy density at frequency $f$ and propagation direction $\theta$, $t$ is time, $C_g$ is the wave group velocity vector, and $S_i$ represents the source–sink terms consisting of wind input, dissipation, nonlinear wave–wave interaction, and bottom effects. From Eq. (1), the discretized two-dimensional (frequency by direction) wave spectrum is generated at each time step and grid point during a simulation (Hubertz 1992). The integration is performed on a land–sea mesh derived from...
a latitude–longitude grid including finite depths for each grid point (TC03). Standard output from the wave model includes, but is not limited to, the significant wave height ($H_s$), the mean and dominant wave period ($T_p$), and the mean wave direction ($T_d$) at user-specified grid points in the model domain.

Wave growth in the WISWAVE model is based on the Phillips and Miles mechanism (Phillips 1957; Miles 1957) and propagation is achieved using a first-order finite-difference scheme (TC03). Nonlinear wave–wave interactions in the source function ($S_i$) are parameterized in WISWAVE in which the momentum flux to the forward face of the spectrum (i.e., frequencies lower than the spectral peak) is based on a constant proportion of energy transferred out of the midrange frequencies. This is a notable difference between the 2G and 3G wave models in that the nonlinear interactions are explicitly accounted for in the 3G models. These nonlinear interactions are known to play a critical role in wave growth processes (e.g., Phillips 1960; Hasselmann et al. 1973); however, efforts to incorporate an accurate representation of these interactions into numerical wave models in a computationally efficient manner are still ongoing (e.g., Van Vledder 2006; Tolman et al. 2005, Tolman 2008). For further information regarding the physics of the WISWAVE model, see Hasselmann et al. (1973), Kitaigorodskii (1983), and Resio and Perrie (1989).

c. Domain configuration

In order for the wave energy to be properly represented in a wave model, the model domain should extend to and cover the full wave-generation area. As an alternative, wave energy that was generated from an outside source can be reproduced by the use of boundary conditions. Here, no boundary data are used; thus, no wave energy is allowed to propagate into the domain. Given that the GOM is a relatively closed basin, any wave energy that may have developed outside of the boundaries and propagated into the domain is assumed to be negligible here. The model domain (see Fig. 1 in Part I) extends from (18°N, 98°W) at the southwestern point to (30.5°N, 81.4°W) at the northeastern point and consists of a 0.09° × 0.09° latitude–longitude grid (185 × 139 grid points) that takes into account Earth’s curvature. Experiments in which the approximate 10-km horizontal grid was increased (not shown) did not improve the results enough to outweigh the computational costs.

d. Wave model

1) Configuration

Model data (i.e., topography, wind forcing, and input parameters) were processed as per the format specified by the WISWAVE user’s guide (Hubertz 1992). This section describes this process and briefly discusses the selection of the input parameters that are provided in Table 1. The time step (DT) is chosen such that the Courant–Friedrichs–Lewy (CFL) condition is satisfied. Here, DT is set by dividing the horizontal grid spacing (DL) by the group speed ($C_g$) of the waves with the longest possible period (assumed to be 20 s). For verification, 10 proximity model locations are selected to compare with GOM NDBC buoys (Fig. 1). Because the buoy locations do not exactly coincide with the model grid points, output from the four surrounding model points is selected and bilinearly interpolated to the buoy locations. The expected height of the wind forcing is 10 m. Wave model output is made available hourly so as to coincide with that of most of the buoy measurements. The wind forcing is updated every 3 h, matching the availability of the NARR product. As a matter of practicality, no attempt was made to interpolate to a shorter time window. In the recent literature, 1-h forcing is found to be typical for high wind–wave forecasting (e.g., Tolman et al. 2005; Chao et al. 2005; Fan et al. 2009; Sampson et al. 2010) while Hanson et al. (2009) use a 3-h interval. However, all of these studies have spatial resolutions on the order of 25 km (or larger in some cases). Here, a large number of wave model simulations (and analyses) would be required to generate a full ensemble, even using 3-h forcing. A 3-h forcing window may be problematic in some cases, especially in conditions where wave containment is occurring (e.g., Bowyer and MacAfee 2005) or if there are significant changes in storm intensity, speed, or structure. While hourly forcing would likely improve the model’s ability to capture the temporal fluctuations associated storm movement, it is computationally expensive at the resolution used here and prohibitive within the context of a large

<table>
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ensemble forecast. The option to update water levels, which is intended for storm surge applications, is not used here.

For this application, 36 (10° each) angle bands and 25 frequency bands (ranging from 0.05 to 0.40 s⁻¹) are selected to represent the discretized wave spectrum. The default number of directional bins in WISWAVE is 16 (22.5°). Given the high wind variability and the associated space and varying swell characteristics, a higher directional resolution is implemented here as the default is likely insufficient to fully represent the TC wave spectrum (e.g., Wright et al. 2001; Phadke et al. 2003, hereafter PH03). Tests in which the wave forecasts are examined with respect to directional resolution are discussed in section 3a.

The midband frequency values are chosen so as to represent all periods of the expected wave energy. It is desirable to have on the order of two to three bands lower than the lowest expected peak energy band in order to best define the shape of the spectrum in the low-frequency or forward-face region (Hubertz 1992). In addition, a spectral resolution that is too coarse can lead to nonphysical discontinuities in the swell fields, which may grow as the swell propagates (Rogers 2002). The frequency bands (corresponding to wave periods ranging from 2.5 to 20 s, respectively) were selected based on an analysis of historical NDBC buoy data for specific TC events in the GOM. The frequencies are not incremented logarithmically, as in the work of others (e.g., Moon et al. 2003). However, a finer spectral resolution is implemented at frequencies corresponding to wave periods above 10 s, as most of the TC wave energy is expected to reside in this frequency range. No sensitivity tests were performed on varying the number of frequency bands or the spacing between the bands. Ultimately, the spectral resolution may be changed or tuned in order to improve the model results. For example, the frequencies modeled could be chosen to match those that the NDBC buoys use to discretize the wave spectrum. However, the frequencies selected here appear to give reasonable results (see section 3a).

2) DRAG COEFFICIENT

It is well known that the air–sea momentum flux parameterizations in even the most advanced numerical wave models have been extrapolated to high wind speeds based on findings under weak-to-moderate wind speed conditions [less than 25 m s⁻¹; e.g., Large and Pond (1981)]. This extrapolation leads to an unrealistic ratio of the neutral drag-to-enthalpy exchange coefficients in TCs, an important component in determining the strength of a TC whereby the generation of total kinetic energy, and thus changes in TC intensity, is modulated by momentum fluxes from the atmosphere to the ocean (e.g., Emanuel 1995; Donelan et al. 2004). In recent years, there have been numerous studies (e.g., Powell et al. 2003; Moon et al. 2004a–c, 2007; Black et al. 2007) examining the behavior of the drag coefficient \( C_d \) in extreme wind conditions (i.e., above 30 m s⁻¹). Field observations performed by Powell et al. (2003) showed that the tendency was for a decrease in \( C_d \) at wind speeds greater than 33 m s⁻¹, and a large decrease as wind speeds approached 51 m s⁻¹. This is thought to be caused by a foam layer that develops on the sea surface as wind speeds approach 50 m s⁻¹, which acts to impede the transfer of momentum from the wind to the sea surface (Powell et al. 2003). As well, Moon et al. (2004a–c) used a coupled wind–wave model and found that \( C_d \) levels off, or even decreases, at wind speeds exceeding 30 m s⁻¹, which is in general agreement with the results of Powell et al. (2003). By incorporating this new parameterization into the Geophysical Fluid Dynamics Laboratory (GFDL) coupled hurricane–ocean prediction model, Moon et al. (2007) found that, while having minimal impact on the TC central pressure, the GFDL model-predicted wind–pressure relationship was improved for strong TCs. In addition to the \( C_d \)–wind speed relationship, Moon et al. (2004b) found that \( C_d \) is also strongly dependent on the TC wave field and varies in the azimuthal direction based on wave age and steepness.

Figure 2 depicts the default \( C_d \) parameterization in WISWAVE, which monotonically increases with increasing wind speed. The \( C_d \) parameterizations of Large and Pond (1981) along with those of Moon et al. (2007) and Powell et al. (2003) are also shown in Fig. 2 for comparison. Tests are performed where the \( C_d \) parameterization
in WISWAVE is capped at different wind speed thresholds ranging from 20 to 30 m s\(^{-1}\). Furthermore, at lower wind speeds, the slope was adjusted to better fit the \(H_s\) observations. The \(C_d\) parameterization that is capped at 30 m s\(^{-1}\) (referred to as the adjusted \(C_d\) hereafter) is also shown in Fig. 2. No tests were performed in which \(C_d\) varies with the TC wave field. This issue and its potential impact on the results are discussed further in section 4.

3. Results

a. Directional resolution

The TC wave field is highly complex as the swell characteristics vary by quadrant and radial distance from storm center (e.g., Wright et al. 2001). Hence, the number of directional bins is important in order to resolve the wave spectrum. Using a stationary idealized TC, PH03 performed sensitivity tests in which the number of direction bins was varied in the WAM wave model. While these studies indicate that the typical number of direction bins used in global and regional wave models (on the order of 24) is adequate to resolve the wind–wave spectrum in the TC core, representing the swell requires additional bin resolution (PH03). In part, this is a result of the increasing bin width with increasing distance from the TC (where the swell propagates). Using the analysis of choice (AOC) winds (Part I), two sensitivity tests are performed in which the number of direction bins is increased from 16 to 36 for TC Rita (2005). The hindcast \(H_s\) and \(T_p\) for the two simulations were compared to observations at the 10 NDBC buoy locations shown in Fig. 1. The National Hurricane Center (NHC) official track for Rita is also shown in Fig. 1 (gray plus signs). Consistent with PH03, the maximum \(H_s\) is not very sensitive to the directional resolution of the model (not shown). In an attempt to isolate the swell component from that of the wind, \(T_p\) is evaluated at two distal buoys, 42019 and 42020, in the northwest GOM. This provides a better assessment of the impact of the directional resolution due to the increased bin sizes with distance from the storm center. Although the timing of the swell arrival at buoy 42020 is spot on for both simulations (Fig. 3, top), it can be seen that, in this case, the increase in directional resolution better resolves the swell \(T_p\) for forecast hours 72 to 96 (F72–F96). This is not the case at buoy 42019 (Fig. 3, bottom), where there appears to be little difference between the two simulations. In general, for the subset of modeled storms, there were only small differences in \(T_p\) (at the time of swell arrival). Although both simulations capture the timing of the swell arrival, they miss the peak observed \(T_p\), tend to underestimate \(T_p\) during the initial stages of the simulation (i.e., F00–F48), and overestimate \(T_p\) during the latter portion after the TC center
has passed the buoy. In terms of the latter, at 42020, the wave model is slow with the transition from swell-dominated to local wind-driven waves as Rita approaches. Hence, it appears as if the model is either underpredicting the spectral energy associated with the local winds, or overpredicting the easterly swell. No wave model spinup is performed and the absence of boundary forcing precludes the propagation of swell into the GOM. Given the relatively closed nature of the basin, we believe this impact, for the most part, is limited. However, the simulations were intentionally started early to allow for some nominal wind–wave development. Here, when the TC center is outside of the model domain, the wave forcing is provided solely by the NARR (no parametric winds).

It is likely that the sensitivity to the directional resolution would increase for a larger basin as the bin size grows with distance. From an operational perspective, increasing the directional resolution is not likely sufficient to counter the additional computational costs, especially because our focus is on forecast wave heights rather than period. Nonetheless, despite what appears to be only a marginal benefit as a result of increased directional resolution, we opt to use 36 bins for all hindcasts presented here.

b. Drag

Simulations using a subset of storms, the AOC wind forcing, and the default $C_d$ parameterization resulted in wave heights that were too large when compared with measurements from NDBC buoys. Conversely, when forced with the NARR-only wind fields, which can severely underestimate the true TC intensity (e.g., see Fig. 7a in Part I), WISWAVE performed quite well when using the default $C_d$. This finding is consistent with that of others regarding compensating errors (e.g., Tolman et al. 2005). Based in part on these results, sensitivity tests are performed in order to examine the impact of the adjusted $C_d$ parameterization (Fig. 2). Three TCs are modeled—Rita (2005), Ike (2008), and Ivan (2004)—also using the AOC wind forcing. At two NDBC buoy locations for which the storms passed nearly directly overhead, $H_s$ time series are generated. The $H_s$ from the simulation using the adjusted $C_d$ parameterization is compared with that using the default $C_d$ (Fig. 4).

In two of the three cases (Rita and Ike), the $H_s$ bias and root-mean-square deviation (RMSD) improve using the adjusted $C_d$ (Table 2). However, despite the rather significant wind increase in the Ivan analysis (Fig. 9a in Part I), the model wave heights were already biased low using the default $C_d$, and thus placing a cap on the drag further limits the wave growth and results in an even larger negative $H_s$ bias. In particular, as Ivan approached within 100 nautical miles (n mi, or 185 km) of the buoy, its storm-relative quadrant shifts from the right to the left front, where the largest wave heights were observed ($\times$ symbols in Fig. 4a). As in Part I, the quadrants are defined relative to storm motion and begin with the right front (Q1) increasing counterclockwise to the right rear.
(Q4; see Fig. 10 in Part I). The negative $H_s$ bias in these two quadrants (Q1 and Q2) is consistent with later results when “all” strong storms are considered (section 3c). During Ivan, the observed $H_s$ at NDBC buoy 42040 (Fig. 4a) and other wave gauges deployed by the Naval Research Laboratory (Wang et al. 2005) surpassed the 100-yr return period often used for designing offshore structures (Panchang and Li 2006). Although the statistics shown in Table 2 include a portion of the Ivan time series (Fig. 4a) for which NDBC buoy 42040 broke free of its mooring and began to drift southwest around 2100 UTC (F129) on 15 September 2004 (Stone et al. 2005), the model low bias clearly precedes the detachment. What is not clear, however, is how much of the low bias near and after storm peak is an artifact of the buoy losing its anchor.

For the Rita simulation (Figs. 4b), $H_s$ tends to be overforecast (high bias) using both $C_d$ parameterizations (Table 2). The largest differences between the forecast and observed $H_s$ occur after the storm’s passage (F96–F120) when buoy 42001 is located in the rear-right quadrant (Q4). The analysis wind speeds (at 42001) are actually lower than observed for part of the time window (F84–F96) in which $H_s$ is overforecast (Fig. 11b in Part I). While the observations appear to support a second small $H_s$ peak (and wind increase) following the closest passage at F84 (see × symbols in Fig. 4b), the model $H_s$ increase is amplified. The overforecast appears to be somewhat unusual in that, overall, the $H_s$ bias is negative in Q4 when all storms are considered (section 4c). However, the buoy location with respect to Rita’s track is very close to Q3, where $H_s$ is found to be consistently high biased for the entire storm set. Thus, given this proximity, it is possible that quadrant 3 waves may have some influence on the positive $H_s$ bias. During the latter portion of the window (F102–F120) the storm has made landfall and is weakening rapidly with best-track maximum winds ($v_{\text{max}}$) decreasing from 90 to 30 kt (where 1 kt = 0.514 m s$^{-1}$). The forecast $H_s$ during the 12-h window surrounding Ike’s closest approach at F72 is relatively good (Fig. 4c). However, $H_s$ is higher than observed both prior to (F48–F66) and after (F78–F90) the storm passage. The wave model overforecasts $H_s$ even though the analysis maximum wind speed at the buoy (60 kt) is well below the best-track $v_{\text{max}}$. While Ike’s intensity is relatively unchanged (the best-track $v_{\text{max}}$ varies from 85 to 95 kt; see Fig. 4c) during its closest approach to the buoy, the storm undergoes rather significant changes in $r_m$, which ranges between 10 and 80 n mi (see Fig. 4 in Part I). Despite these fluctuations, the wind analysis is reasonably good at 42001, indicating that the high bias may not be related to the local wind field. During F48–F66, the buoy was located to the left of the storm track in Q2, while for F78–F90 the buoy is in Q3 and then Q4. The later period appears to be somewhat of an exception in that the overall statistics indicate that the model is low biased in Q4 for all statistical stratifications (section 3c). However, as in the Rita simulation, the buoy is in close proximity to Q3 throughout the latter portion of the time window and even transitions back into Q3 around F102. The rather sharp decrease (on the order of a meter) in $H_s$ around F60 prior to the closest approach of TC Ike is a result of the wind analysis. The parametric wind field drops off a little too rapidly and undershoots the NARR, producing a spurious decrease in $H_s$ (Fig. 11c in Part I). The latter time window (F102–F120) encompasses the landfall of Ike, which is accompanied by a rapid decrease in intensity.

Although the $C_d$ parameterization presented here is more in line with recent observations (e.g., Powell et al. 2003), it is possible that either $C_d$ should decrease at high wind speeds or that the $C_d$ cap should be set lower than 30 m s$^{-1}$. The impact of the latter is examined by running simulations for the three TCs with $C_d$ capped at 20 and 25 m s$^{-1}$. For both Ike and Rita, where $H_s$ is over-forecast, both the RMSD and bias increase as the wind speed at which $C_d$ is capped increases, while for Ivan the opposite is true (not shown). The high bias in the $H_s$ time series for these storms appears, in part, to be related to the buoys’ locations in the left and rear quadrants near the TC center. In contrast, as Ivan approaches buoy 42040 from the south, the buoy remains primarily in the front-right quadrant, moving into the front-left region just prior to landfall. The model tends to be low biased in these quadrants for both strong storms and those with an $r_m$ larger than 20 n mi. The quadrant-dependent bias is investigated in more detail in the next section. We did not attempt to run a simulation with $C_d$ decreasing at high wind speeds. Tests for which the $C_d$ cap was varied (not shown) were limiting in that the results were improved in some storm quadrants and degraded in others. Based on these results (and the current literature), it seems more prudent to argue for a quadrant-varying $C_d$.

c. Wave model evaluation

The $H_s$ bias, RMSD, and scatter index (SI) statistics are composited using the 10 GOM NDBC buoys (Fig. 1)
and all storms. NARR-only error statistics are also provided for comparison purposes. In addition to the bulk statistics, results from the 12 TC simulations (Tables 3 and 4 in Part I) are evaluated at radii within 100 n mi of the TC center and stratified based on maximum storm strength (Saffir–Simpson), radius of maximum wind \( r_{\text{rmw}} \), and storm speed \( C_d \). With the exception of the latter, the statistics are also sorted into four storm-relative quadrants. The data distribution, by quadrant, is given for \( r > 100 \) n mi in Table 3. TC hindcasts forced with high quality wind fields can yield \( H_s \) estimates with a bias less than 0.5 m, a mean absolute error less than 1.0 m, and SI values on the order of 15% or less for deep ocean sites (Cardone et al. 2000).

1) BULK WAVE STATISTICS

Table 4 contains bulk error statistics, the total amount of buoy data used for validation, and the number of missing observations for all storms and no distance restrictions. The NARR \( H_s \) bias is near zero while the analysis produces wave heights that are biased slightly high (7 cm). However, the RMSD is about 6 cm lower for the analysis. These results are consistent with the bulk wind statistics in which the NARR \( U_{10} \) bias (RMSD) is slightly lower (higher) than the analysis. The SI is consistent with the RMSD, both of which are slightly lower for the AOC. The small differences are a direct result of the majority of observations being outside of the TC core and thus dominating the statistics (e.g., Swail and Cox 2000). To isolate the impact of the analysis on the wave forecasts, the statistics are hereafter presented only for observations that lie within 100 n mi of the storm center.

2) STRATIFIED WAVE STATISTICS

The bias, RMSD, and SI for the NARR and analysis-generated \( H_s \) are presented in Fig. 5 and Table 5 for moderate (Saffir–Simpson categories 1–2) and strong (Saffir–Simpson categories 3–5) TCs. The NARR exhibits relatively low \( H_s \) bias and RMSD outside of the 100-n mi radius. However, within the 100-n mi radius, the NARR is low biased in all quadrants, especially to the right of the storm motion for moderate storms where the \( H_s \) biases are \(-3.5 \) and \(-1.9 \) m in the right-front (Q1) and right-rear (Q4) quadrants, respectively. The analysis is also low biased in the right quadrants \((-2.1 \) and \(-0.2 \) m), but much less so than the NARR. The NARR SI is largest for the left side (Q2–Q3) of the strong storms. The analysis yields lower SI, but it remains high in Q3 (0.40). Comparing quadrants for the NARR forcing only, the right-side bias is actually less for the strong storms \((-1.1 \) and \(-1.4 \) m) than the moderate TCs, while the left-front quadrant (Q2) exhibits lower bias for the moderate storms and comparable results in the left rear (Q3). The analysis \( H_s \) RMSD and SI are improved in each of the quadrants in both storm categories. In terms of the RMSD, the largest analysis improvements occur in the right quadrants of the moderate storms where the analysis values are about half that of the NARR. That the improvement is maximized for moderate storms is, in part, a result of the 30 m s\(^{-1}\) cap on \( C_d \), which limits the impact of the wind analysis on the wave field for strong storms. For strong storms, the analysis bias is lower than the NARR in all but Q3, while for moderate storms the results are split with the NARR outperforming the analysis in Q2 and Q3 (to the left of storm motion). In these two quadrants, the analysis wave heights are both biased slightly high (0.7 m), despite an improved wind field that has little or even a slightly low bias in these quadrants (0.1 and \(-0.9 \) m s\(^{-1}\); see Part I). Conversely, for moderate storms, the NARR produces low \( H_s \) bias \((-0.3 \) and \(-0.2 \) m) in the presence of relatively large wind biases in Q2 and Q3 \((-5.0 \) and \(-4.4 \) m s\(^{-1}\); see Part I). These inconsistencies in the wave model performance seem to preclude any simple model improvements. For example, changing the drag parameterization by either increasing \( C_d \) for low wind speeds or extending the cap to wind speeds greater than 30 m s\(^{-1}\) improves the low bias in Q1 while simultaneously increasing the positive bias in Q2 and Q3 (not shown). However, the AOC yields an overall bias reduction for both storm categories (the “all” column in Table 5). As mentioned previously, \( C_d \) may also depend on wave age and steepness.
FIG. 5. Storm-relative error statistics (by quadrant) using the background (NARR, filled triangles) and analysis (BLND, filled squares) for (left) moderate and (right) strong storms. NARR statistics (top) $H_s$ bias (m), (middle) $H_s$ RMSD (m), and (bottom) SI for data inside (black fill) and outside (gray fill) of a 100-n mi radius are shown.
This would likely result in an azimuthally varying $C_d$ due to surface roughness variations, even in the absence of wind asymmetries. This is discussed further in section 4. A more fundamental approach would necessarily involve the inclusion of a hydrodynamic model that accounts for wind–wave–current interaction. While important within the context of understanding the underlying physics (e.g., spatially varying stress), this approach is not pragmatic for generating large ensembles.

The $H_s$ statistics are presented for all TCs and stratified with respect to the best-track $r_m$ (Table 6). Here, $r_m$ is used because it is related to TC size and thus to the analysis filter width [$D$, Eq. (9) in Part I]. A value of 20 n mi is used to delineate between storms, with those greater than or equal to (less than) 20 n mi referred to as RMG20 (RML20). Compared to RMG20, the NARR $H_s$ RMSD for the RML20 storms is lower for all quadrants with the exception of Q4, despite much larger wind speed errors (Table 8 in Part I). The analysis $H_s$ RMSD is lower in all quadrants for both categories with the largest decreases in Q1 and Q4. The SI is largest on the left side of RMG20, and lowest for RML20 storms with values near the 15% threshold generated by high quality wind fields. Overall, the bias reduction is about a meter for both $r_m$ categories (the all column in Table 6), with the largest improvement in Q4. However, the analysis produces degraded results in two of the left quadrants: Q3 for RMG20 and Q2 for RML20.

We also briefly examine the impact of the storm speed $C_s$, for strong and moderate TCs combined. The asymmetric structure of the TC wind field is a function of $C_s$ (e.g., Schwerdt 1979). In addition, the wave containment time and thus wave enhancement are critically linked and extremely sensitive to $C_s$ with optimum storm speeds on the order 10–15 kt (Bowyer and MacAfee 2005). To ensure comparably sized datasets, a 10-kt threshold was chosen and storms with an instantaneous $C_s$ greater than or equal to (less than) 10 kt are referred to as fast (slow) TCs. Here, the storm-relative statistics are composited with respect to the right and left quadrants only. While the $H_s$ bias is relatively large (negative) in the right quadrant for fast TCs, the analysis reduces the $H_s$ bias in both quadrants (right and left) compared to the NARR (Table 7). The largest improvement occurs in the right quadrant for slow TCs, where the analysis bias is 1.2 m less than the NARR. The analysis produces only a slight improvement in the $H_s$ RMSD in the left quadrant compared to that of the right despite a comparable (and large) reduction in wind speed RMSD (of 6 m s$^{-1}$) in both quadrants of the slow TCs (Fig. 6, bottom right). For fast TCs, the

<table>
<thead>
<tr>
<th>$H_s$</th>
<th>Moderate (category 1–2)</th>
<th>Strong (category 3–5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q1</td>
<td>Q2</td>
</tr>
<tr>
<td>NARR bias</td>
<td>-3.52</td>
<td>-0.30</td>
</tr>
<tr>
<td>BLND bias</td>
<td>-2.08</td>
<td>0.68</td>
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<tr>
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<td>4.12</td>
<td>1.70</td>
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<td>BLND RMSD</td>
<td>2.70</td>
<td>1.41</td>
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<tr>
<td>NARR SI</td>
<td>0.27</td>
<td>0.30</td>
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<tr>
<td>BLND SI</td>
<td>0.22</td>
<td>0.22</td>
</tr>
<tr>
<td>No. of data points</td>
<td>28</td>
<td>44</td>
</tr>
</tbody>
</table>

Table 5. Storm-relative $H_s$ error statistics, by quadrant, for the background (NARR) and analysis (BLND) as a function of storm intensity (moderate and strong). Statistics shown are for radii < 100 n mi only. The “all” columns represent the totals for the four quadrants.

<table>
<thead>
<tr>
<th>$H_s$</th>
<th>RMG20</th>
<th>RML20</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q1</td>
<td>Q2</td>
</tr>
<tr>
<td>NARR bias</td>
<td>-2.07</td>
<td>-1.14</td>
</tr>
<tr>
<td>BLND bias</td>
<td>-1.34</td>
<td>-0.11</td>
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<tr>
<td>NARR RMSD</td>
<td>3.10</td>
<td>2.79</td>
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<tr>
<td>BLND RMSD</td>
<td>2.25</td>
<td>2.14</td>
</tr>
<tr>
<td>NARR SI</td>
<td>0.28</td>
<td>0.40</td>
</tr>
<tr>
<td>BLND SI</td>
<td>0.22</td>
<td>0.33</td>
</tr>
<tr>
<td>No. of data points</td>
<td>61</td>
<td>56</td>
</tr>
</tbody>
</table>

Table 6. Storm-relative $H_s$ error statistics for the background (NARR) and analysis (BLND) as a function radius of maximum wind $r_m$ for moderate and strong storms combined. RMG20 (RML20) represents storms with $r_m \geq (<) 20$ n mi. Statistics shown are for radii less than 100 n mi only. The all columns represents the totals for the four quadrants.
impact of the analysis on the RMSD appears to be similar for both quadrants (Fig. 6, bottom left). The bias decrease (between 0.5 and 1 m) is similar for the two quadrants for both fast and slow TCs (Fig. 6, top). Despite a much lower wind speed bias and RMSD, the analysis $H_s$ bias is actually slightly worse than the NARR in the left quadrant of slow TCs. Similar to the results for the storm intensity and $r_m$, the left sides of the TCs yield the largest SIs, especially the fast storms. Within the current paradigm, it would be difficult to improve both the wind field and $H_s$ in the left quadrant of slow TCs given that the NARR-forced wave simulations produce a near-zero $H_s$ bias in the presence of an 8 m s$^{-1}$ low bias in the wind field (Fig. 6, top right).

4. Discussion

Wave hindcasts for 12 tropical cyclones are forced using a wind analysis derived from a combination of the NARR and a parametric wind model. In Part I, the wind field was tuned by varying the analysis parameters so as to reduce the wind speed bias. Using 3 of the 12 storms and this “best” wind field, the wave model drag parameterization and directional resolution were tuned, in part, to reduce errors in the significant wave height. Simulations were then run for the 12 storms and statistics were composited by storm-relative quadrant and stratified by physically relevant quantities including radius of maximum winds, storm speed, and storm intensity. Our findings indicate the following.

a. $H_s$ bias is most negative (i.e., biased low) in the right quadrants

The $H_s$ bias in the right quadrants is more than a meter larger than the left for the fast TCs despite a comparable (and negative) wind speed bias. The bias is also negative for both right quadrants in each of the statistical subcategories (storm intensity and radius of maximum wind). In particular, the largest bias (negative) is in the right-front quadrant for the moderate and RMG20 storms. The low bias may result from using a climatological (and first order) asymmetry parameter (Part I), which may not fully represent the actual TC wind asymmetry. The asymmetry depends on the storm translation speed, which is also an important factor in determining the spatial distribution of the directional wave spectrum (Moon et al. 2003). More importantly, the asymmetry and storm translation speed have both been shown to accentuate the difference in the drag coefficient between the front-right and rear-left storm quadrants (Moon et al. 2004b). Another possibility is that the mixed layer velocity (i.e., current) is strongly biased (high) on the right side of a TC where there is a resonance between the time-evolving wind stress vector and wind-driven inertial oscillations (Price 1981). Ultimately, these differences would need to be accounted for in the stress calculations and thus would require a fully coupled (wind-wave–current) system.

b. $H_s$ is high biased in the rear-left quadrant

Regardless of the data stratification, WISWAVE overforecasts $H_s$ in the left-rear quadrant even though the analysis wind field is underforecast. Moon et al. (2004b) suggest that lower, shorter, and younger waves in the rear-left quadrant produce lower sea drag when compared with other storm quadrants, an effect that tends to be amplified as the storm translation speed increases. (Our results indicate that the model bias is actually higher for slow TCs.) Furthermore, dominant waves often propagate at angles that vary with respect to the local wind, which, in turn, may impact the magnitude of the wind stress. When compared to the buoys, the model appears to capture the directional spread of the waves in Q3 at distances greater than 100 n mi from the storm center (Fig. 7a). Near the storm center (i.e., at radii less than 100 n mi), the model peak wave direction is offset, with the model (observed) maximum count in the 150°–180° (90°–120°) directional bin (Fig. 7b). Because the model and buoy peak wave directions shown are storm relative (and expressed using the meteorological wind direction convention), this corresponds to a model peak wave direction more in line with the direction of the TC motion whereas the buoys depict the waves traveling at an angle to the left with respect to storm motion (Fig. 8). Directional wave spectra reported in the literature are consistent with both of these maxima (see, e.g., Wright et al. 2001). However, the mean storm-relative wind direction is northwesterly
(315°) in this quadrant (Fig. 8), nearly opposite the buoy peak wave direction while the model peak is more cross-wise with respect to the wind. Given that the observed wind (and thus the wind stress) opposes the peak wave direction may, in part, explain the positive model bias in this quadrant.

c. Other issues and findings
- The relatively coarse resolution of the wave forecast grid was examined in which the grids were reduced to 6 km. This had only a minor impact for the three test storms (Ike, Ivan, and Rita).
A relatively large number of direction bands were chosen to resolve the discretized wave spectrum. However, tests in which the wave forecasts are sensitive to changes in the directional resolution showed little sensitivity.

No sensitivity tests were performed on varying the number of frequency bands or spacing between the bands. Ultimately, the spectral resolution may be changed or tuned in order to improve model results. For example, the frequencies modeled could be chosen to match those that the NDBC buoys use to discretize the wave spectrum.

The approach taken here is to design and assess a simple and computationally efficient wind–wave forecast system that can be used to generate unbiased ensemble wave forecasts for extreme storm events. Depending on the length and spread of the forecast, the background vortex can be extracted (e.g., Sampson et al. 2010) and the wind field hole filled. The forcing (wind analyses) would then be generated, for a given forecast time, via a combination of the redacted wind field and parametric vortex model as prescribed by the relevant parameters from operational NHC Monte Carlo simulations (DeMaria et al. 2009). A viable ensemble forecast system will depend implicitly on whether one can produce a wave forecast that lies within the range of observational errors given a reasonably accurate wind field. Based on a limited number of observations, improvements in the wave height forecast are gleaned as a result of downscaling the NARR winds and the wave model tuning. However, the paradigm in which the...
drag coefficient is dependent solely on the wind speed is somewhat limiting in this respect. No direct attempts were made to directly address this or a number of other issues associated with wave modeling in general (e.g., numerics, physics). Many of these are discussed in detail by Cavaleri (2009) but are beyond the scope of this study.

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