
Fuqing Zhang, Yonghui Weng, Jason A. Sippel and Zhiyong Meng
Department of Atmospheric Sciences, Texas A&M University, College Station, Texas

Craig H. Bishop
Marine Meteorology Division, Naval Research Laboratory, Monterey, California

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Corresponding author address: Dr. Fuqing Zhang, Department of Atmospheric Sciences, Texas A&M University, College Station, TX 77845-3150. Email: fzhang@tamu.edu
Abstract

This study explores the assimilation of Doppler radar observations for cloud-resolving hurricane analysis, initialization and prediction with an ensemble Kalman filter (EnKF). The case studied is Hurricane Humberto (2007), the first landfalling hurricane in the US since the end of the 2005 hurricane season and the most rapidly intensifying near-landfall storm in US history. The storm caused extensive damage along the southeast Texas coast but was poorly predicted by operational models and forecasters. It is found that the EnKF analysis, after assimilating radial velocity observations from three WSR-88D radars along the Gulf coast, closely represents the best-track position and intensity of Humberto. Deterministic forecasts initialized from the EnKF analysis, despite displaying considerable variability with different lead times, are also capable of predicting the rapid formation and intensification of the hurricane. These forecasts are also superior to the operational forecasts and simulations without radar data assimilation. Moreover, nearly all members from the ensemble forecasts initialized with EnKF analysis perturbations predict rapid formation and intensification of the storm. However, large ensemble spread of peak intensity, which ranges from a tropical storm to a category-two hurricane, echoes limited predictability in deterministic forecasts of the storm and the potential of using ensembles for probabilistic forecasts of hurricanes.
Abstract

This study explores the assimilation of Doppler radar observations for cloud-resolving hurricane analysis, initialization and prediction with an ensemble Kalman filter (EnKF). The case studied is Hurricane Humberto (2007), the first landfalling hurricane in the US since the end of the 2005 hurricane season and the most rapidly intensifying near-landfall storm in US history. The storm caused extensive damage along the southeast Texas coast but was poorly predicted by operational models and forecasters. It is found that the EnKF analysis, after assimilating radial velocity observations from three WSR-88D radars along the Gulf coast, closely represents the best-track position and intensity of Humberto. Deterministic forecasts initialized from the EnKF analysis, despite displaying considerable variability with different lead times, are also capable of predicting the rapid formation and intensification of the hurricane. These forecasts are also superior to the operational forecasts and simulations without radar data assimilation. Moreover, nearly all members from the ensemble forecasts initialized with EnKF analysis perturbations predict rapid formation and intensification of the storm. However, large ensemble spread of peak intensity, which ranges from a tropical storm to a category-two hurricane, echoes limited predictability in deterministic forecasts of the storm and the potential of using ensembles for probabilistic forecasts of hurricanes.
1. Introduction

Landfalling hurricanes are among the deadliest and costliest natural hazards. Over the past decade, significant progress has been made in short-range track forecasts of tropical cyclones. The current-day average 48-h forecast position is as accurate as a 24-h track forecast 10 years ago (Franklin 2004). However, there is virtually no improvement in our ability to predict hurricane intensity in terms of minimum sea-level pressure, maximum wind speed or amount of precipitation (Houze et al. 2007). We thus have very limited skill in predicting tropical cyclone formation, rapid intensification, fluctuation or decay (Elsberry et al. 2007). High-resolution cloud-resolving mesoscale models, along with better initialization of the initial vortex, may be necessary to faithfully represent the internal dynamics that is crucial for hurricane intensity forecasts (Houze et al. 2007; Chen et al. 2007; Davis et al. 2008).

Despite improvements in using advanced data assimilation methods with or without initial vortex bogussing, our ability to initialize a tropical cyclone with dynamically consistent structure and intensity remains limited, even with the assimilation of radar observations (e.g., Zou and Xiao 2000; Pu and Braun 2001; Xiao et al. 2007). Numerical weather prediction models also have known difficulties in “spin-up” of a tropical cyclone or hurricane vortex with appropriate moisture, diabatic and divergence structure at the initial time. Part of the difficulty of hurricane initialization comes from the lack of routine 4-dimensional observations with sufficient spatial and temporal resolution to represent the initial hurricane structure and intensity. Another part of the difficulty comes from the deficiency of the current generation operational data assimilation systems, which use static background error covariance. The mostly balanced, isotropic, flow-independent background statistics derived from long-term averages of past short-term forecast error (Parrish and Derber 1992) are ill-suited for the highly flow dependent
background error covariances associated with tropical cyclones. In addition, operational models generally have insufficient model resolution to effectively incorporate high-resolution convective scale observations (such as those from radars) for cloud-resolving hurricane prediction. Physical (diabatic) initializations using rainfall, radar and/or satellite observations is a promising approach (Krishnamurti et al. 2001), though its effectiveness in spinning up a full hurricane vortex for cloud-resolving hurricane prediction remains to be fully explored.

The ensemble Kalman filter (EnKF) is a state-estimation technique that uses short-term ensemble forecasts to estimate flow-dependent background error covariance or other probabilistic aspects of the background forecast. It was first proposed by Evensen (1994) and has been adopted for data assimilation of many disciplines in geosciences and beyond (Evensen 2003; Hamill 2006). For the past few years, the feasibility and performance of the EnKF have been demonstrated through both simulated and real-data observations ranging from convective scales using radar observations (e.g., Snyder and Zhang 2003; Zhang et al. 2004; Dowell et al. 2004; Tong and Xue 2005) to mesoscale and regional scales (e.g., Zhang et al. 2006; Torn et al. 2006; Meng and Zhang 2007; Fujita et al. 2007; Meng and Zhang 2008a,b). The benefits of directly estimating forecast covariances are also likely to increase with the next generation of NWP models that resolve scales at which physical balances are not amenable to stationary, isotropic covariance models currently used for operational forecasts.

The current study explores for the first time the use of EnKF to directly assimilate Doppler radar radial velocity observations for cloud-resolving hurricane analysis and prediction, both deterministically and probabilistically. The case to be examined is Hurricane Humberto (2007), the first landfalling hurricane in the United States since the end of the 2005 hurricane season and the most rapidly intensifying near-landfall storm in US history. Humberto
strengthened from a 40-mph depression at 12Z September 12, 2007 to a 92-mph hurricane at 07Z September 13, a 52-mph increase in surface wind speed in only 19 hours. The storm caused extensive damage along the southeast Texas coast and was poorly predicted by operational models and forecasters. The real-time forecast by the operational global forecast system (GFS) running at National Centers for Environmental Prediction (NCEP) failed to capture the intensification and genesis of the storm (Fig. 1). The Weather Research and Forecast (WRF) model also failed in post-event, 4.5-km, cloud-resolving simulations that were initialized with the GFS analyses (as in the control ensemble analysis and forecast detailed in subsequent sections) with lead times every 6 h from 6 to 48 h.

At different stages of formation and intensification, Humberto was within range of coastal WSR-88D radars at Corps Christi (KCRP) and Houston-Galveston (KHGX) in Texas and Lake Charles (KLCH) in Louisiana. These radars provided valuable convective-scale observations of the storm but were not assimilated by real-time NCEP operational models. This study is among the first to apply the EnKF to assimilate real-data radar velocity observations for complex weather phenomena exhibiting different scales of motion (moving beyond a single supercell storm examined in Dowell et al. 2004). The following section will introduce the forecast model, the EnKF technique and the processing of the observations to be assimilated. Section 3 presents the use of the EnKF for this storm in terms of analysis quality, deterministic and ensemble forecasts. Comparison to the performance of data assimilation with a 3-dimensional variational method that assimilates the same radar observations in the WRF model is given in section 4. Concluding remarks are given in section 5.
2. Methodology

2.1 The forecast model: WRF

The advanced research WRF (ARW) is used in this study. WRF is a fully compressible, nonhydrostatic mesoscale model (Skamarock et al. 2005). The vertical coordinate follows the terrain using hydrostatic pressure, and the model uses an Arakawa-C grid. Prognostic variables are column mass of dry air, velocities (u, v, w), potential temperature, geopotential, and mixing ratios for water vapor, cloud, rain, ice, snow, and graupel.

In the control experiments, three model domains with two-way nesting are used. The coarse domain covers the contiguous United States with 160x121 grid points and a grid spacing of 40.5 km, and the inner domain D2 (D3) cover the central United States with also 160x121 (253x253) grid points and a grid spacing of 13.5 (4.5) km (Figure 2). All model domains have 35 vertical layers, and the model top is set at 10 hPa. The physical parameterization schemes include the Grell-Devenyi cumulus scheme (Grell and Devenyi 2002), WRF Single Moment 6-class microphysics with graupel (Hong et al. 2004), and the Yonsei State University (YSU) scheme (Noh et al. 2003) for planetary boundary layer processes. The NCEP GFS operational analysis at 00Z 12 September and its forecast are used to create initial and boundary conditions. Data assimilation is performed for all domains but all verification is performed for D3.

2.2 The data assimilation method: EnKF

The EnKF implemented in the WRF model is the same as that in Meng and Zhang (2008a,b) except that no multi-scheme ensemble is used for this study. This version of the filter was originally implemented in the Penn State University-National Center for Atmospheric Research mesoscale model version 5 (MM5) documented in Zhang et al. (2006). It uses the covariance relaxation of Zhang et al. (2004) to inflate the background error covariance. Different from the
standard inflation method (Anderson 2001) in which all points in the prior field are inflated, this relaxation method only inflates the covariance at updated points via a weighted average between the prior perturbation (denoted by superscript \( f \)) and the posterior perturbation (denoted by superscript \( a \)) as follows:

\[
(x_{\text{new}}^a)' = (1 - \alpha)(x^a)' + \alpha(x^f)'
\]  

(1)

The weighting coefficient, \( \alpha \), is set to 0.5 in the OSSE studies of Zhang et al. (2004; 2006). Considering that prior error in real-data applications may be larger due to unavoidable imperfections in the forecast model (Whitaker et al. 2008; Meng and Zhang 2008a,b), a value of 0.8 is used for the present study.

2.3 Ensemble initial and boundary perturbations

Although the optimum ensemble size to estimate the forecast uncertainty is still under active research, 30 members are used herein. An ensemble size of 20-50 was found to be affordable and reasonable based on previous studies (e.g., Houtekamer and Mitchell 2001; Anderson 2001; Snyder and Zhang 2003; Zhang 2005; Zhang et al. 2006; Meng and Zhang 2007; Meng and Zhang 2008a,b). As in Zhang et al. (2006), the initial ensemble is generated with WRF-3DVar using the cv3 background error covariance option (Barker et al. 2004). To create a largely balanced perturbation, we first generate a set of random control vectors with a normal distribution (zero mean and unit standard deviation). Then the control increment vector is transformed back to model space via an EOF transform, a recursive filter and physical transformation via balance equations. The perturbed variables include horizontal wind components, potential temperature, and mixing ratio for water vapor, and their error statistics are defined by the climatological background error covariance. Other prognostic variables such as vertical velocity (\( w \)) and mixing ratios for cloud water (\( q_c \)), rain water (\( q_r \)), snow (\( q_s \)) and graupel
(q_g) are not perturbed. The perturbation standard deviations thus generated are approximately 2 m s\(^{-1}\) for horizontal wind components (\(u\) and \(v\)), 0.8 K for temperature (\(T\)), 1 hPa for pressure perturbation (\(p'\)), and 0.8 g/kg for water vapor mixing ratio (\(q\)). The 3DVar perturbations are added to the GFS analysis to form an initial ensemble, which is then integrated for 9 h to develop an approximately realistic, flow-dependent background error covariance structure before the first observation is assimilated. Similar methods, using 3DVar to generate the initial ensemble for the EnKF, are also employed in Houtekamer et al. (2005) and Barker (2005).

The simplest way to perturb lateral boundary conditions for a limited area model is to use a global ensemble forecast with a correct size and resolution (which is usually unavailable; Chessa et al. 2004). Torn et al. (2006) examined several alternative boundary perturbation methods and concluded that the error originating from using different methods is limited to near the edges of the domain. In this paper, the GFS operational forecasts are used to create boundary conditions that are perturbed in the same manner as with the initial ensemble.

2.4 Super observations and quality control

With large volumes of radar observations that are recorded at a much higher resolution than the forecast model grid spacing for the EnKF data assimilation, significant data thinning and quality control of observations become necessary. The process of combining multiple observations into one high-accuracy “super” observation (SO) is often referred to as “superobbing”. A SO for radar radial velocity is created through horizontal averaging in polar space of the raw polar volume of data (Lindskog et al. 2004; Albers 1995). To minimize horizontal correlations of the SOs, each pixel of the raw data is allowed to influence one SO only. To avoid averaging of radial velocity (Vr) in significantly different directions, the averaging bin is confined within 5 km in radial direction and 5° in azimuthally direction.
For quality control of the observations, we first use the NCAR radar editing software SOLO to dealiase the range-folded data and to remove apparently erroneous observations. We then implement the following additional quality control measures in the SO generation for this study: 1) any raw observations with values smaller than 2 m/s or with distances to the radar smaller than 4 km will be discounted; 2) a raw Vr observation will be discounted if the deviation from the bin mean exceeds twice of the standard deviation of all raw observations in the bin; 3) there shall be at least 4 valid Vr raw observations within an averaging bin; 4) there will be no SO for a bin whose standard deviation is twice the average of the standard deviations in all bins; 5) the final SO value of the bin will be the average of at most 10 raw observations that are closest to the center of the bin. In the processing of EnKF analysis, the observation error of all SOs are assumed to be 3 m/s in this study, and an SO will also be discounted if the difference between this SO and the forecast prior is larger than 5 times the observation error.

2.5 Successive covariance localization

A successive covariance localization (SCL) technique is designed to assimilate dense radar observations that contain information about the state of the atmosphere at a wide range of scales. The method is also designed to reduce computation cost and sampling errors. This technique uses the Gaspari and Cohn (1999) fifth-order correlation function for covariance localization, but a different localization radius of influence (ROI) is used for different groups of observations by random sampling. SCL assumes that both large and small-scale errors are simultaneously present. First, one tries to remove dynamically important aspects of the large scale error by assimilating a relatively small subset of observations with a large ROI. Next, the ROI is made smaller, and higher density observations are used to constrain both smaller-scale errors and what remains of the large-scale error. The process is repeated until all scales resolved
by the observational network have been adequately dealt with. The SCL method has some resemblance to the successive correction method used in some earlier empirical objective analysis schemes (e.g., Barnes 1964), though in the EnKF the same observation will not be used twice. Extensive sensitivity experiments that demonstrate the benefits of using the SCL method over using single ROIs for all observations will be presented elsewhere. No vertical localization was used in this study.

In this particular case, we first use a horizontal ROI of 1200 km for 10% of super observations (SOs) to capture the large-scale background flow in all 3 domains. We then use an ROI of 400 km for 20% of SOs to represent the mesoscale flow (i.e., tropical cyclone scale) in the 2nd and 3rd domains. Last, we use an ROI of 130 km for 60% of SOs to capture even smaller scale phenomena that include mesoscale vortices just in the 3rd domain. The vertical ROI is 34 in the unit of vertical grid levels (with varying height distance; as in Zhang et al. 2006) for all the 3 domains. The other 10% of the observations are used for additional sensitivity experiments and verifications to be presented elsewhere.

3. EnKF performance

3.1 EnKF analyses

The control EnKF experiment begins to assimilate the super observations (SOs) from the Corpus Christi (KCRP) and Houston-Galveston (KHGX) WSR-88D radars at 0900 UTC 12 September 2007 (i.e., 09Z/12, the same notation will be used hereafter), 6 h before the tropical depression status was declared by National Hurricane Center (NHC). The EnKF continues to assimilate SOs from these two radars every hour until 18Z/12. After this time, the KCRP radar is too far from the storm to have significant impact while the Lake Charles (KLCH) radar begins to have significant coverage of the storm. The KLCH radar observations are thus assimilated
beginning at 19Z/12. The EnKF assimilation continues every hour until 12Z/13, a few hours after the storm in the NHC best track reaches its peak intensity and starts weakening over land. The number of SOs assimilated from the three radars by the EnKF at different times and example distributions of the SOs at 09Z/12 and 19Z/12 are shown in Figure 3.

Figure 4 shows time evolution of the minimum sea-level pressure (“minSLP”) and maximum surface wind speed (“maxWSP”) estimated from the posterior EnKF mean analysis field (gray; hereafter referred to as “the EnKF analysis”) as well as the average (red) of maximum/minimum values estimated from each ensemble member’s posterior (green) in comparison to the NHC best track analyses (black). Minimum SLP in the EnKF analysis (gray) agrees well with the average of members’ minimum values (red) due to collocation of the centers of most members. Both the mean and individual members also compare very favorably with the NHC best track analysis. However, due to strong spatial and temporal variability of the maximum surface wind speed, maxWSP in the EnKF analysis (gray) is significantly smaller than that of the average (red) of members’ maxima. Yet, the average of each member’s maxWSP (red) matches well with the NHC best track estimate (black). We therefore believe it is more appropriate to use the averages of maxWSP and minSLP from each member for verifying ensemble forecasts in terms of extreme values.

There is large ensemble spread of both minSLP and maxWSP among the analysis members (Fig. 4). Standard deviation of minSLP (maxWSP) increases from 1-2 hPa (1-3m/s) at the first few assimilation cycles to 10-11 hPa (7-8m/s) at the peak intensity time (not shown). Likewise, the minSLP (maxWSP) at the peak intensity time varies from 992 hPa (27 m/s) to 960 hPa (49m/s). In terms of corresponding intensity category, this represents a range from a strong tropical storm to a category 2 hurricane. Large disparities between ensemble members
demonstrate significant EnKF analysis uncertainties during and after the rapid intensification of Humberto.

Despite the large spread, data assimilation with an EnKF is clearly beneficial. All analysis ensemble members capture the rapid storm formation and intensification when EnKF assimilates Vr observations. This is in strong contrast to pure ensemble forecasts started with the same prior perturbations but without EnKF assimilation of Vr (hereafter refer to as “NoDA”). The NoDA ensemble neither captures the mean development nor the realistic uncertainties associated with the mean forecast (blue curves in Fig. 4).

Figure 5 compares the observed 0.5-degree base scan of radial velocity from KHGX (only 1/10 of the observations plotted) with corresponding simulated values from both the EnKF analysis and the NoDA ensemble forecast mean valid at 09Z/12, 18Z/12, and 03Z/13. The benefit of assimilating Vr observations with EnKF is evident even after the first volume of observations is assimilated at 09Z/12. The analyses at this time capture the coastal mesoscale circulation much better than the NoDA ensemble mean. Since NoDA at 09Z/12 is simply the EnKF prior estimate with no Vr observations assimilated, a comparison of Fig. 5c-d shows the immediate benefit of the EnKF at the initial assimilation time. Subsequently, the EnKF well analyzes the cyclone vortex structure, intensity and evolution (Fig. 5). Apparent additional mesoscale details are captured with more data assimilated at each hour (analysis increments; not shown).

Figure 6 shows a comparison of radar reflectivity from the observed composite, the EnKF analysis and the NoDA ensemble forecast mean valid at 12Z/12, 00Z/13 and 12Z/13, respectively. The impact of Vr observation assimilation on the unobserved reflectivity variable is evident in the progressively better posterior estimates (analysis means) of reflectivity. At 12Z/12,
while the NoDA ensemble forecast mean simulates a broader area of light precipitation, the EnKF analysis begins to localize the precipitation into two primary bands. The first band is located along the Gulf coast of Texas and Louisiana to the east and northeast of Houston, and the other is further west but far south of the display domain. This compares much more favorably to the observations (though the convection in the EnKF analysis is still weaker and broader partly due to the ensemble averaging effects discussed above).

At 00Z/13, during the storm’s rapid intensification, the EnKF analysis captures an impressive developing tropical cyclone south of KHGX with multiple spiral rainbands to the north and east quadrants fueled by warm moist air from the south. Except for a spurious onshore mesoscale rainband right across Texas and Louisiana border, the position, intensity and structure of the rainbands, including the developing eyewall in the EnKF analysis (Fig. 6e), compare remarkably well with the observed reflectivity (Fig. 6d). At 12Z/13, the final analysis time after the storm begins its rapid weakening over land, the EnKF analysis correctly places the center of the storm over the Texas/Louisiana border. It also correctly analyzes the broad rainbands to east of the storm (Fig. 6g, h). The NoDA ensemble forecast mean, on the other hand, does not simulate any tropical development (Fig. 6c, f, i).

3.2 Deterministic forecasts from the EnKF analysis

Next we examine the value that using EnKF to assimilate Vr adds to forecasts. Single, deterministic forecasts from the CNTL EnKF mean analyses are performed every 3 hours from 09Z/12 to 12Z/13. These simulations are integrated until 12Z/14.

Figure 7 shows the simulated cyclone position, minSLP and maxWSP in deterministic WRF forecasts initialized with EnKF analyses at different times. Despite a slight delay in peak intensity compared to the best track estimates, all forecasts initialized with EnKF analyses
simulate significant tropical cyclone formation and intensification if WSR88D Doppler observations are assimilated for 9 h or longer. On average, continuous assimilation through time and assimilating more observations produces both better analyses of the initial storm and better deterministic track and intensity forecasts. These WRF forecasts from the EnKF analyses are in strong contrast to the near complete forecast failure by NCEP/GFS operational forecasts and WRF forecasts (with the same model configuration) initialized with the GFS analyses at all lead times (Fig. 1). This signifies the importance and potential of assimilating radar observations to improve cloud-resolving tropical cyclone initialization and prediction at all lead times.

Among the simulations initialized from the mean EnKF analyses, forecasts from 18Z/12 and 21Z/12 are the most remarkable. The peak intensity of both simulations (which have significant lead times) is within 2 hPa of the observed (best-track) peak intensity. Also, the maximum surface winds in both runs reach or nearly reach Category 1 hurricane intensity, which is less than 5 m/s different from the best-track estimates. Both forecasts are considered to be quite successful given the uncertainties in the best track estimate and since a relatively small number of forecast times are used for determining the simulated intensity.

The slight delay in the peak intensity for all forecasts reflects a slight lag in the simulated landfall time compared to best-track observations. Despite the bias, the 36-h track error is less than 50-km at the observed peak time for the forecast initialized at 18Z/12. This is smaller than the average NHC operational track forecast error. Broadly speaking, the initial positions and subsequent track errors in the EnKF analyses become smaller as the radar data assimilation cycle proceeds.

Figure 8 compares observed composite radar reflectivity with corresponding simulated reflectivity in deterministic forecasts. The forecasts are initialized at 09Z/12 with the EnKF prior
(mean) and at 18Z/12 after 9-h of EnKF analysis and are valid at 21Z/12, 03Z/13 and 09Z/13. Consistent with the track and intensity forecasts shown in Fig. 7, the deterministic forecast from the EnKF analysis mean compares favorably with radar observations in terms of structure and placement of rainbands and formation of the eyewall right before moving over the coast. These phenomena are non-existent in the forecast without EnKF assimilation of Vr observations (Fig. 8c, 8f, 8i). The forecast without data assimilation also develops widespread convection over the Gulf region across the display domain, but the convection is highly disorganized with only weak cyclonic circulation in the center. While the above forecast from the EnKF analysis is far better, it is also far from perfect. For example, it underpredicts the outer spiral rainband to the far east of the storm, partly because this forecast is initialized at 18Z/12, before the KLCH radar observations are assimilated.

3.3 Deterministic forecast with a 1.5-km movable nested domain

Since the 4.5-km control experiments only marginally resolve moist convection, we perform another high-resolution experiment that nests an additional domain with 1.5-km horizontal grid spacing ("1.5KM"). Experiment 1.5KM has a fourth domain of 253x253 grid points centered on the maximum vorticity and moves with the tropical cyclone using a vortex tracking method (Chen et al. 2007) and two-way nesting. Experiment 1.5KM is initialized at 18Z/12 with the same EnKF analysis from the 4.5-km domain discussed above. Figure 9 shows 1.5KM simulated minSLP and maxWSP in comparison to both the best track estimate and the 4.5-km control experiment starting at the same time. Besides having a slightly slower movement, the simulated track in this 1.5-km forecast is nearly identical to that of the 4.5-km control forecast initialized at the same time (Fig. 9a). The intensity is slightly weaker in terms of minSLP (Fig. 9b) and is comparable in terms of maxWSP (Fig. 9c). The difference is well within
the uncertainties in the EnKF analysis (Fig. 4), and the ensemble forecasts started at the same time with the EnKF analysis perturbations (next subsection).

Although the storm in 1.5KM is slightly weaker in terms of peak intensity, Fig. 10 shows that the higher-resolution simulation captures much more realistic detailed mesoscale structure (e.g., 00Z/13 and 06Z/13) of the cyclone. This additional structure compares more favorably to the observed radar reflectivity at different stages of the cyclone development than that of the 4.5-km control forecast depicted in Fig. 8. In particular, it is only the F1.5 km run that captures the strong asymmetry of the observed reflectivity at 06Z/13. Future studies will perform high-resolution forecasts at different times and/or utilize the EnKF analysis on the 1.5-km model domain.

3.4 Ensemble forecasts from EnKF analysis

Large variation between deterministic forecasts initialized with the EnKF mean analysis at different times and the difficulty in real-time operational forecasting suggest predictability of this storm is rather limited. The EnKF analysis helps to understand this predictability problem because it provides consistent, flow-dependent uncertainties that are used for initializing ensembles for probabilistic prediction.

A 30-h ensemble forecast is initiated with the control EnKF analysis and perturbations at 18Z/12. Consistent with the large variation between deterministic forecasts starting with EnKF at different times (Fig. 7), there is also large spread among different members from the EnKF-initialized ensemble. This is shown in Fig. 11, which plots the evolution of position, minSLP and maxWSP simulated by all members and the deterministic forecast initialized from the EnKF analysis (mean). The spread of minSLP triples over 30 hrs from less than 1.5 hPa at 18Z/12 (the initial time) to 4.5 hPa at 09Z/13, while the spread of maxWSP grows from 1.6m/s to 6.3m/s
during the same period (not shown).

The large forecast uncertainty and sensitivity to initial perturbation uncertainties can also be clearly seen in Fig. 12, which shows a scatter plot of minSLP in the ensemble members at 18Z/12 (i.e., the initial time for the ensemble) versus minSLP at 09Z/13 (i.e., a 15-h forecast near the peak intensity time). The strong correlation (~0.7) between initial minSLP and minSLP at the time of peak intensity highlights the importance of the initial analysis accuracy. The initial ensemble spread at 18Z/12 is comparable to or even smaller than typical errors in the best track estimates, which further demonstrates the limited predictability of deterministic forecasts even after radar observations are assimilated. Thus, the need for probabilistic/ensemble forecasting of tropical cyclones is clear.

To further exemplify error growth between ensemble members, Figure 13 shows the simulated dBZ from one of the weakest members (#29) and one of the strongest members (#31) at 18Z/12 and 09Z/13 (based on minSLP at 09Z/13; marked on Fig. 12). Despite having apparently similar structure and strength at 18Z/12, the two members diverge tremendously by 09Z/13, again signifying large uncertainties in deterministic forecasts of hurricanes. Forecast uncertainties could be even larger given that model error, which is considerable, is not included in the current study.

Ongoing studies are currently investigating both the mechanism leading to rapid tropical cyclone formation and intensification and the dynamics that leads to the rapid error growth for this event. Recently studies revealed that upscale growth of moist convection, such as in the form of vortical hot towers, may play a critical role in internal dynamics (Krishnamurti et al. 2005; Montgomery et al. 2006). Limited predictability of moist convection could ultimately limit the predictability of tropical cyclones (Sippel and Zhang 2008; Zhang and Sippel 2008), as is the
case for extratropical cyclones (Zhang et al. 2002; 2003; 2007; Tan et al. 2004) or continental warm-season mesoscale convective systems (Zhang et al. 2006; Hawblitzel et al. 2007; Bei and Zhang 2007).

4. Comparison with WRF/3DVar

Since the data assimilation schemes used in operational forecast models at NCEP at the time of Humberto were based on the three-dimensional variational method (3DVar), here we use the WRF model and its 3DVar system to assimilate exactly the same observations for a comparison with the EnKF analysis discussed above.

The WRF-3DVar method used here was developed primarily at NCAR, and it is now operational at the Air Force Weather Agency (Barker et al. 2004). Its configuration is based on an incremental formulation, producing a multivariate analysis in the model space. Its incremental cost function is minimized in a preconditioned control variable space where the errors of different control variables are largely uncorrelated. As in any other variational data assimilation technique, the structure of the background error covariance may play a very important role in 3DVar. We use the WRF/3DVar default background error statistic (its “cv” option 3 originated from an earlier version of the NCEP/GFS system). The first guess comes from the 9-h WRF 4.5-km (single, deterministic) forecast initialized with the GFS/FNL analysis at 00Z/12. WRF/3DVar begins assimilation at 09Z/12 and continues to assimilate exactly the same Vr SO observations as in the EnKF analysis hourly until 18Z/12, after which time a 30-h forecast without further data assimilation is performed.

Figure 14 shows the evolution of minSLP and maxWSP from the WRF/3DVar experiment in comparison to the corresponding EnKF analysis and forecast. Although both 3DVar and EnKF assimilate exactly the same observations with the same model resolution, the 3DVar experiment
fails to perform satisfactorily. This result is in spite of the fact that 3DVar has a better fit of maximum wind speed at 18Z/12 before the pure forecast starts. We acknowledge that the performance of 3DVar may be further improved through further tuning of the background error covariance and/or with the addition of initial vortex bogussing (Q. Xiao at NCAR, personal communications), but the sensitivity of the performance of 3DVar to different configurations and representations of background error statistics is beyond the scope of this study. On the other hand, there may still be room to improve the performance of EnKF through further tuning, which is also beyond the scope of the current study.

5. Summary and conclusion

This study explores the uses of Doppler radar observations for cloud-resolving hurricane analysis, initialization and prediction with an ensemble Kalman filter (EnKF). The case studied is Hurricane Humberto (2007), the first landfalling hurricane in the US since the end of the 2005 hurricane season and the most rapidly intensifying near-landfall storm in US history. The storm caused extensive damage along the southeast Texas coast but was poorly predicted by operational models and forecasters. It is found that the EnKF analysis, after assimilating radial velocity observations from three WSR-88D radars along the Gulf coast, closely represents the best-track position and intensity of Humberto. Deterministic forecasts initialized from the EnKF analysis, despite having considerable variability with different lead times, are also capable of predicting the rapid formation and intensification of the hurricane. These forecasts are superior to operational forecasts, simulations without radar data assimilation, and forecasts initialized with assimilation of the same observations with a three-dimensional variational method implemented with the same forecast model. Moreover, ensemble forecasts initialized with EnKF analysis perturbations before the rapid intensification show large spread among ensemble
members. Such large spread further exemplifies significant uncertainties in deterministic prediction of the hurricanes, especially the intensity forecast.

In this study, EnKF demonstrates great promise in assimilating Doppler radar observations to initialize hurricanes with detailed, accurate mesoscale structure. Even though ground-based radar may only have limited range to provide observations for hurricane prediction with lead times beyond 24 hours, this may be complemented with airborne radar with Doppler observations and longer lead times that will soon become available for all hurricane aircraft reconnaissance missions (F. Marks at NOAA/HRD, personal communications).

Future studies are planned to examine the dynamics and predictability of Humberto with the EnKF analysis and forecasts. Despite the promising performance of both deterministic and probabilistic forecasts from the EnKF analysis, the intrinsic limit of hurricane predictability (i.e., in face of nearly perfect observations and initialization) remains unclear in terms of both track and intensity forecasts. It also remains unclear what observations are necessary and sufficient to define the initial tropical cyclone vortex and large-scale environment. Answers to these questions have strong implications related to how society might better distribute resources to combat future hurricane-related disasters. This is extremely important given that the number of hurricanes and their intensity/destructiveness are reportedly on the rise with the warming climate (Emanuel 2005; Webster et al. 2005).

The limit of formation/intensity predictability given realistic initial condition and model errors (which are still large at present) in numerical weather prediction models may be alleviated through improving our understanding of dynamics and physics, development of better numerical models, improved data coverage and assimilation techniques. However, there always will be forecast errors due to the inherent limit of predictability arising from initial errors with
amplitudes far smaller than any observation and analysis system (e.g., Zhang and Sippel 2008); these are errors that society will always have to cope with (Pielke 1997).

Such inherent uncertainties in hurricane forecasts highlight the need for developing advanced ensemble prediction systems to provide event-dependent probabilistic forecasts and risk assessment. In practice, despite an increasing role and demonstrated benefits of using ensembles in aiding deterministic hurricane forecasting (Kristnamurti et al. 1999), the uncertainty issued with today’s operational hurricane forecasts is still based on averaged climatological errors and thus is not case-dependent. This case clearly demonstrates that uncertainty can be quite large at some times (e.g., Sippel and Zhang 2008), and having access to such information in the operational environment would serve forecasters well.

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References:


Figure Captions

**Fig. 1** Time evolution of (a) Minimum sea-level pressure and (b) maximum surface wind forecasts by operational GFS forecasts (blue) starting every 6 hours from 00Z/12 to 00Z/13 and by 4.5-km WRF forecasts (red) starting from the operational GFS analyses in comparison to the NHC best track estimate (black).

**Fig. 2** Configuration of the WRF model domains 1, 2 and 3 with horizontal grid spacings of 40.5, 13.5 and 4.5 km, respectively. Also depicted are the NHC best-track estimate of Humberto with intensity color-coded and the three WSR-88D radar locations.

**Fig. 3** (a) The number of SOs from each radar assimilated at different times by the control EnKF experiment and the exemplar distributions of SOs at (b) 09Z/12 and (c) 19Z/12.

**Fig. 4** Time evolutions of (a) minimum sea-level pressure and (b) maximum surface wind speed estimated from the EnKF analysis and NoDA ensemble forecast. Thin green (cyan) lines represent the maximum/minimum values estimated from each ensemble member of EnKF analysis (NoDA forecast) with thick red (blue) line represents the average of maximum and minimum values in each member. The gray line indicates the estimated from the EnKF analysis mean while the black curve is the NHC best track estimate.

**Fig. 5** The raw radial velocity observations from the 0.5-degree base scan of the KHGX radar (OBS; left panels), the corresponding EnKF analysis (middle panels) and the NoDA ensemble forecast mean (right panels) valid at 09Z/12, 18Z/12 and 03Z/13, respectively.
**Fig. 6** Comparison of the radar reflectivity (dBZ) from the observational composite mosaic (OBS; left panels), the corresponding EnKF analysis (middle panels) and the NoDA ensemble forecast mean (right panels) valid at 12Z/12, 00Z/13 and 12Z/13, respectively.

**Fig. 7** The simulated (a) positions, (b) minimum SLP and (c) maximum surface wind of Humberto in the deterministic WRF forecasts (color curves) initialized with the EnKF analyses every 3 hours from 12Z/12 to 12Z/13 in comparison with the NHC best track estimate (black).

**Fig. 8** Comparison of radar reflectivity (dBZ) from observational composite mosaics (OBS; left panels), the deterministic forecast initialized with the EnKF analysis at 18Z/12 (middle panels), and with the NoDA ensemble forecast mean (right panels) valid at 21Z/12, 03Z/13 and 09Z/13, respectively.

**Fig. 9** The simulated (a) position, (b) minimum SLP and (c) maximum surface wind of Humberto from the 1.5-km deterministic forecast initialized with the EnKF analysis at 18Z/12 (“1.5KM”) in comparison with the 4.5-km forecast and the best track estimate.

**Fig. 10** Comparison of radar reflectivity (dBZ) from observational composite mosaics (OBS; left panels) with those derived from the 4.5-km control forecast (middle panels) and the 1.5-km forecast (right panels) valid at 00Z/13 and 06Z/13, respectively.
**Fig. 11** The simulated (a) position, (b) minimum SLP and (c) maximum surface wind of Humberto by ensemble forecast initialized with the EnKF perturbations at 18Z/12 (each member in green) in comparison to the deterministic forecast initialized from the EnKF mean analysis (red) and the NHC best track estimate (black). Analysis and uncertainty until 18Z/12 are also shown in dashed curves.

**Fig. 12** The scatter plot of forecasted minimum SLP at 18Z/12 (x axis; 0 h) and 09Z/13 (y axis; 15 h) in different ensemble members with the weakest and strongest members at 09Z/13 highlighted.

**Fig. 13** The comparison of simulated maximum reflectivity (dBZ) derived from the strongest member (left) and the weakest member (right) of the ensemble valid at 18Z/12 and 09Z/13, respectively.

**Fig. 14** The simulated (a) position, (b) minimum SLP and (c) maximum surface wind of Humberto from the deterministic forecast initialized with the WRF/3DVar analysis at 18Z/12 in comparison with the 4.5-km forecast from the EnKF analysis and the best track estimate.
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