Ensemble Data Assimilation Applied to RAINEX Observations of Hurricane Katrina (2005)

RYAN D. TORN AND GREGORY J. HAKIM
University of Washington, Seattle, Washington

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ABSTRACT

An ensemble Kalman filter (EnKF) based on the Weather Research and Forecasting model is applied to generate ensemble analyses and forecasts of Hurricane Katrina (2005) and the surrounding area every 6 h over the lifetime of the storm on a nested domain. Analyses are derived from assimilating conventional in situ observations, reconnaissance dropsondes, including data taken during the Hurricane Rainband and Intensity Exchange Experiment (RAINEX), and tropical cyclone position estimates. Observation assimilation at individual times consistently reduces errors in tropical cyclone position, but not necessarily in intensity; however, withholding observations leads to significantly larger errors in both quantities. Analysis increments for observations near the tropical cyclone are dominated by changes in vortex position, and these increments increase the asymmetric structure of the storm. Data denial experiments indicate that dropsondes deployed in the synoptic environment provide minimal benefit to the outer domain; however, dropsondes deployed within the tropical cyclone lead to significant reductions in position and intensity errors on the inner domain. Specifically, errors in the inner domain ensemble-mean 6-h forecasts of minimum pressure are 70% larger when dropsonde data is not assimilated. Precipitation fields are qualitatively similar to Tropical Rainfall Measuring Mission (TRMM) satellite estimates, although model values are double the values of the satellite estimate. Moreover, the spinup period and initial imbalance in EnKF-initialized WRF forecasts is less than starting the model from a GFS analysis. Ensemble-mean 48-h forecasts initialized with EnKF analyses have track and intensity errors that are 50% smaller than GFS and NHC official forecasts.

1. Introduction

One method of improving numerical weather prediction (NWP) model forecasts of tropical cyclones (TCs) is to produce better initial conditions by combining observations with a model forecast via data assimilation. Most operational data assimilation systems employ quasi-fixed error statistics to spread observation information to model grid points, which are often not appropriate for the TC environment. Given this difficulty, several different techniques have emerged where either a “bogused” vortex is inserted into the analysis (e.g., Kurita et al. 1995), or the TC is repositioned to the best-track location during data assimilation (e.g., Liu et al. 2000). These procedures have been tuned to work well for synoptic-scale TC forecasts, but are not adequate for creating meso- and convective-scale analyses and forecasts of the storm, particularly for short lead times. The lack of appropriate initial conditions for storm-scale models may contribute to the lack of improvement in TC intensity forecasts during the past 15 yr (Rogers et al. 2006).

The ensemble Kalman filter (EnKF) is an attractive approach for TC state estimation because this technique assimilates observations using flow-dependent error statistics, which capture the strong spatial variability near TCs. These flow-dependent error statistics, which control the weight given to observations relative to a short-term forecast and how observational information affects model variables near the TC, should allow for corrections to the TC structure and position without the need for the special techniques described above. Several studies (e.g., Houtekamer et al. 2005; Whitaker et al. 2008; Szunyogh et al. 2008; Torn and Hakim 2008) have shown that assimilating real observations with an EnKF...
leads to forecasts that are competitive with operational data assimilation systems that incorporate significantly more data, while Zhang et al. (2009) obtained a superior forecast of Hurricane Humberto (2007) by assimilating coastal radar observations with an EnKF. Since the EnKF produces an ensemble of equally likely analyses, TC ensemble forecasting is straightforward, and does not require perturbing deterministic analyses. The interested reader is directed to Evensen (2003) and Hamill (2006) for reviews of the EnKF.

Here we test an EnKF for TC forecasting by implementing such a system to generate analyses and forecasts over the life of Hurricane Katrina (2005). Observations taken during the Hurricane Rainband and Intensity Change Experiment (RAINEX; Houze et al. 2006) provide an opportunity to test the performance of an EnKF for TC forecasting with an unusually rich set of observations. Ensemble analyses and forecasts are generated on a coarse-resolution outer domain, and on a nested, higher-resolution inner domain.

We begin with an overview of the model setup and data assimilation system in section 2. Results for the coarse outer domain are presented in section 3, and the nested inner domain results are shown in section 4. A summary and concluding discussion is given in section 5.

2. Experiment setup

Gridded analyses of Hurricane Katrina and the surrounding locations are generated every 6 h by cycling an EnKF from 0000 UTC 22 August 2005 (42 h prior to designation as a tropical depression) to 0000 UTC 30 August 2005 (6 h after landfall). The analysis ensemble is advanced in time using version 2.1.2 of the Advanced Research Weather Research and Forecasting (ARW-WRF) model (Skamarock et al. 2005) on a nested domain. The outer domain has 30-km horizontal grid spacing and covers the eastern United States and the northern Caribbean Sea (Fig. 1). The inner domain has 10-km horizontal grid spacing and covers the Gulf of Mexico and Florida during 1200 UTC 26 August–0000 UTC 29 August (Fig. 1). Both domains have 38 vertical levels, and use the following components: WRF three-class microphysics scheme (Hong et al. 2004), Kain–Fritsch cumulus parameterization scheme (Kain and Fritsch 1990), Yonsei University (YSU) boundary layer scheme (Hong et al. 2006), and the Noah land surface model (Ek et al. 2003).

An ensemble of lateral boundary conditions for the outer domain is obtained using the fixed-covariance perturbation (FCP) technique of Torn et al. (2006). Ensemble lateral boundary conditions are derived by drawing random perturbations from the WRF VAR system (Barker et al. 2004), which are scaled by 1.7, and subject to a temporal autocorrelation coefficient of 0.4; these values are taken from Torn and Hakim (2008). The perturbations on the lateral boundaries of the outer domain are added to 6-h forecasts of the National Centers for Environmental Prediction (NCEP) Global Forecasting System (GFS). For each inner domain ensemble member, one-way lateral boundary conditions are prescribed by interpolating the corresponding background (prior) forecast from the outer domain onto the boundary points of the inner domain. In addition to cycling the data assimilation system, 48-h ensemble forecasts on the outer domain are generated every 12 h from 0000 UTC 25 August to 0000 UTC 27 August by advancing all 90 members with FCP ensemble boundary conditions; the ensemble mean on the lateral boundaries is set to the GFS forecast initialized at the same time.

Observations are assimilated from Automated Surface Observing System (ASOS) stations, ships, buoys, raw sondes, the Aircraft Communications Addressing and Reporting System (ACARS), and cloud motion vectors (Velden et al. 2005) every 6 h using a square root version of the EnKF (Whitaker and Hamill 2002) for a 90-member ensemble. In general, Katrina moves through an area of relatively low observation density, except when traversing Florida (Fig. 1). Previous studies have shown that $O(100)$ ensemble members are needed to accurately resolve error covariances, while additional members provide minimal improvement (e.g., Whitaker et al. 2004; Dirren et al. 2007). The National Hurricane Center (NHC) TC advisory position (technically the latitude and longitude of lowest sea level pressure) is assimilated every 3 h similar to the method described in Chen and Snyder (2007). The TC latitude (longitude) is compared to the latitude (longitude) of the minimum SLP in each ensemble member’s forecast, and all model state variables are adjusted by this innovation; the NHC position estimates are assumed to have an error standard deviation of 10 km. Observation errors for all other observations are taken from European Centre for Medium-Range Weather Forecasts (ECMWF) statistics, and we assume that dropsonde errors are characterized by radiosondes.

These experiments also assimilate targeted dropsondes deployed by the National Oceanic and Atmospheric Administration (NOAA) Hurricane Research Division (HRD; e.g., Aberson 2002) and the RAINEX field campaign. Since raw dropsonde data often contains high-frequency temporal noise that can be problematic for data assimilation, we assimilate postprocessed data from HRD (e.g., Franklin et al. 1996) for observations deployed within 1 h of an analysis time. Dropsonde drift is accounted for by assimilating the sonde data at the horizontal Global Positioning System (GPS) position of
each vertical level. Coordinated dropsondes deployed by the NOAA P3 and the Naval Research Laboratory (NRL) P3 sampled the structure of the TC, and the NOAA G-IV took observations of the synoptic environment surrounding the storm. The outer domain does not have sufficient horizontal resolution to accurately simulate mesoscale TC structure, which is problematic when observations resolve such features. For example, Aberson (2008) showed that assimilating eye and eyewall dropsonde data at coarse resolution can result in degraded track and intensity forecasts. Therefore observations from the NOAA P3 and NRL P3 are not assimilated on the outer domain. For similar reasons, TC minimum SLP data is not assimilated in these experiments.

Small ensembles have a tendency to produce spurious long-distance covariances and to underestimate covariance magnitude, which we address with the following conventional techniques. Analysis increments are localized on both domains using Eq. (4.10) of Gaspari and Cohn (1999) such that the increments reduce to zero 2500 km from the observation location; vertical localization is not employed. This distance is longer than the value used on a midlatitude domain by Torn and Hakim (2008) in approximate proportion to the increase in Rossby radius. For the outer domain, analysis deviations from the ensemble mean are given by averaging the prior and posterior deviations from the mean with a 0.75 and 0.25 weighting, respectively (Zhang et al. 2004). These weighting factors are determined empirically by performing experiments in which these weights are adjusted until the mean-squared error in ensemble-mean 6-h forecasts (computed with respect to rawinsondes) matches the innovation variance; for an optimal ensemble system, these two values should be equal (Houtekamer et al. 2005). Covariance inflation is not applied to the inner domain because it magnifies asymmetries due to TC position during assimilation; this issue will be discussed further in section 4. Torn and Hakim (2008) describe in more detail how the covariance localization radius and weighting factors are determined for similar EnKF studies.

EnKF experiments with global models are often initialized with random climatological states (e.g., Whitaker et al. 2004; Anderson et al. 2005), but this approach is problematic on limited-area domains because of the mismatch of the domain interior with lateral boundary conditions based on 6-h forecasts. Here, we follow the approach of Dirren et al. (2007) and initialize the outer domain ensemble on 0000 UTC 22 August by adding random, scaled, fixed-covariance perturbations from the WRF VAR system (Barker et al. 2004) to the

FIG. 1. Number of observation reports assimilated by the WRF EnKF within 60 km of each grid point from 0000 UTC 22 Aug 2005 to 0000 UTC 30 Aug 2005 (shading). The dashed line encloses the inner computational domain and the thick solid line is Katrina’s track.
GFS 36-h forecast initialized on 1200 UTC 20 August. The scaling factor for the perturbations (i.e., 1.9) is determined by matching the RMS error in this 36-h forecast to the standard deviation of the WRF VAR perturbations. By the time Katrina is declared a tropical depression (at 1800 UTC 23 August), the 6-h forecast errors with respect to observations come into equilibrium with the ensemble variance, which indicates that the ensemble has little memory of the initial ensemble (shown below). The inner domain is initialized at 1200 UTC 26 August by pairing each inner domain ensemble member to an outer domain ensemble member and interpolating the outer ensemble member onto the inner member’s grid.

To summarize the tuning measures adopted here, covariance averaging is used to increase ensemble spread, and random perturbations are used to populate ensemble lateral boundary conditions. Ensemble spread near the storm is reduced by assimilating NHC advisory position data, and dropsonde observations that resolve mesoscale structure near the storm are only assimilated on the nested domain.

3. Outer domain results

Prior to describing the performance of the WRF EnKF forecasts of TC track and intensity, we present verification statistics for two fields with respect to rawinsonde and ASOS observations within the domain. For 6-h WRF EnKF forecasts, we also calculate the observation innovation standard deviation,1 which should match the RMS error for a well-calibrated ensemble (Houtekamer et al. 2005).

Figure 2 shows that after a 2-day ensemble spinup period, the RMS error and spread in 6-h WRF EnKF 300-hPa zonal wind and altimeter setting forecasts come into statistical equilibrium with the observations; other fields show similar results. Over this period, the average error in 300-hPa wind (altimeter) is 3.6 m s\(^{-1}\) (1.19 hPa), which is 0.4 m s\(^{-1}\) larger (0.5 hPa lower) than the average error in 6-h GFS forecasts during the same period. Whereas the ensemble spread is generally higher than the RMS error for altimeter, the ensemble is well calibrated for the 300-hPa wind. The performance of this filter configuration is similar to the real-time EnKF system described by Torn and Hakim (2008).

Analyses and forecasts are also verified on the outer domain using position and intensity estimates from NHC tropical storm best-track data. Table 1 displays the RMS difference between the NHC best-track position and intensity for the ensemble-mean analysis and background forecast (denoted “control”). These quantities are defined by the grid point of lowest sea level pressure (SLP) in the region near the storm for each ensemble member. On average, the RMS error in TC track is lower for the ensemble-mean analysis than for the background forecast, which indicates that observation assimilation systematically reduces position errors. We note that although position data is assimilated, TC position is not a state variable, thus verifying that the analysis against best-track data provides a check that the flow-dependent error statistics consistently correct the ensemble during assimilation. The largest position errors occur at 0000 UTC 24 August when Katrina is first designated as a tropical depression; however, as the TC intensifies and the circulation becomes better defined, the analysis position errors are consistently less than the horizontal grid spacing. Although these experiments do not assimilate the best-track estimate of TC minimum SLP or maximum surface wind, the RMS errors in minimum SLP for the ensemble-mean analysis and background forecast are less than 15 hPa (Table 1). Furthermore, the error in maximum wind speed\(^2\) is 13 m s\(^{-1}\), which is roughly equivalent to the error in 36-h official NHC forecasts of Katrina (Beven et al. 2008). For most analysis times, the minimum SLP (maximum wind) on the outer domain is higher (lower) than best-track estimates, especially after Katrina undergoes rapid intensification on 28 August.

Table 1 reveals larger errors in the analyses of TC intensity as compared to the background forecast, which indicates that assimilating observations has an adverse impact on TC intensity. To illustrate how a nearby observation affects the TC, Fig. 3 shows the SLP and 500-hPa zonal wind increment due to the 500-hPa wind observation taken by a nearby dropsonde at 0000 UTC 27 August 2005. Assimilating this observation leads to an increase (decrease) in SLP to the west (east) of the TC center, achieving a shift in the position of the storm to the east. For 500-hPa wind, the largest impact is not at the observation location; rather, this observation leads to an increase (decrease) on the northwest and southwest (northeast and southeast) side of the TC, which is consistent with an eastward displacement of the TC. A similar result based on assimilating vortex position was found by Chen and Snyder (2007), and is attributable to the large gradients associated with TC structure. Small

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1 This quantity is defined by the square root of the diagonal elements of \( HP^{-1} H^T + R \), where \( H \) is an operator that maps from model-state variables to observations, \( P \) is the background error covariance matrix, and \( R \) is the observation error variance matrix.

2 Maximum wind speed in the model is found by computing the highest 10-m wind speed within 250 km of the TC center.
changes in position contribute to larger perturbations from the ensemble mean than do storm-centered perturbations in intensity or structure; these perturbations dominate the covariance fields even though the position (minimum SLP) standard deviation is 21 km (4 hPa) at this time. As a result we find that many observations near the TC have a similar increment dipole, indicating that most of the covariance between the TC and surrounding fields is associated with the TC position, rather than TC intensity or structure. To quantify this point, we compute analysis increments in the ensemble-mean SLP due to the sequential assimilation of observations within 800 km of the TC center at 0000 UTC 27 August. These analysis increments are not independent, but rather are conditioned on all previously assimilated observations at the same time. The leading empirical orthogonal functions (EOFs) of these 1000 analysis increments are computed to determine the spatial structures that account for the most analysis-increment variance. The leading analysis increment EOF, which explains 32% of the increment variance, exhibits a northeast–southwest-oriented dipole centered on the TC similar to the single increment shown in Fig. 3a (Fig. 4a). The second EOF, which explains 23% of the variance, also exhibits a dipole centered on the TC, with a different orientation than the leading EOF (not shown). The third EOF (Fig. 4b), as well as the remaining two statistically significant EOFs (e.g., North et al. 1982), explain less than 9% of the variance and are generally related to TC intensity. Repeating the calculation, and withholding the TC position observations, confirms that the first and second EOF are dipoles centered on the TC position, indicating that this result is not due to the TC position data (not shown). Similar patterns are observed for EOFs of analysis increments at other times, although the leading EOFs sometimes reflect a mixture of phase and intensity increments.

Table 1. RMSE in the ensemble-mean analysis and background forecast of tropical cyclone track, minimum sea level pressure, and maximum 10-m wind speed averaged over each domain’s cycling period.

<table>
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<th>TC track</th>
<th>TC min SLP</th>
<th>TC max wind</th>
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<td>Analysis</td>
<td>Background forecast</td>
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<td>Outer domain</td>
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<tr>
<td>Control</td>
<td>22 km</td>
<td>28 km</td>
<td>14.9 hPa</td>
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<tr>
<td>No drop</td>
<td>22 km</td>
<td>28 km</td>
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<td>46 km</td>
<td>24.3 hPa</td>
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<td>Inner domain</td>
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<tr>
<td>Control</td>
<td>17 km</td>
<td>20 km</td>
<td>19.8 hPa</td>
</tr>
<tr>
<td>No drop</td>
<td>18 km</td>
<td>22 km</td>
<td>47.8 hPa</td>
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Fig. 2. Time series of the RMS error in WRF EnKF and GFS 6-h forecasts with respect to (a) rawinsonde observations of 300-hPa zonal wind and (b) ASOS observations of altimeter setting in the domain. The dashed line denotes the square root of the sum of the ensemble variance and observation error variance at the observation locations, the solid line is the RMS error in the ensemble mean, and the dashed–dotted line is the error in the GFS forecast on this domain.
The leading EOFs for other fields are also consistent with a shift in TC position. For 500-hPa zonal winds (Fig. 4c), the leading EOF (27% of variance) is a north–south-oriented tripole pattern centered on the TC center, with the largest magnitude within the gradient in the zonal wind, and is associated with north–south shifts in the TC position. Whereas the second EOF (14% of variance) is a quadrupole pattern, which is consistent with east–west translation in TC position, the third EOF (8% of variance) is maximized at the wind magnitude extremes, and is therefore associated with intensity changes (not shown).

Excessive variance in TC position can have an adverse affect on the shape and intensity of the TC. For example, Fig. 5 shows the 0600 UTC 27 August analysis when assimilating best-track position every 6 h, compared to every 3 h. The 6-h position assimilation has more variance in the TC position, and the resulting asymmetric increments distort the structure of the vortex. This result indicates that TC position observations may have an adverse affect on the analysis when the background TC is more than a few grid points from the best-track position; a similar conclusion is drawn by Chen and Snyder (2007).

The value of cycling the data assimilation system is evaluated by comparison with a deterministic 8-day WRF forecast on the outer domain, initialized on 0000 UTC 22 August using GFS analyses for initial and boundary conditions. The tropical wave that evolves into Katrina fails to intensify into a tropical depression in this simulation (not shown). We conclude that continuous observation assimilation yields analysis corrections that are necessary to capture TC genesis in this case. In a separate experiment, we cycle the EnKF system over the same 8-day period, but withhold dropsonde observations (denoted as “no drop” in Table 1).
In this case, TC position and intensity RMS errors in the background forecast are nearly identical to the control simulation, suggesting that other observations near the TC, such as position data, can compensate for the synoptic dropsondes. In a third cycling experiment, we remove TC position observations from the observation set (“no best track” in Table 1). In these simulations, RMS background TC position, minimum SLP, and maximum wind speed errors are 64%, 79%, and 36% greater, respectively, than the control experiment.

Compared to GFS and deterministic WRF forecasts, the 48-h ensemble forecasts initialized from the WRF EnKF analyses provide consistently better forecasts of Katrina’s track and intensity (Fig. 6). The RMS error in the WRF EnKF ensemble-mean 48-h forecasts of Katrina’s track are 65%, 60%, and 25% lower than the
official NHC forecast, the GFS model, and a WRF forecast, respectively, on the outer domain using initial and boundary conditions from GFS analyses (WRF-GFS). Since the ensemble-mean lateral boundary conditions for the WRF EnKF and WRF-GFS forecasts are identical, differences between these forecasts are mostly due to the initial conditions. A specific example of the track improvements is illustrated in Fig. 7, which shows that WRF EnKF forecasts initialized at 1200 UTC 25 August and 0000 UTC 26 August capture the observed southwesterly motion of Katrina across Florida, whereas the other forecasts have a more westerly track.

WRF EnKF forecasts also have lower errors in TC intensity as compared to the other forecasts considered here. For all forecast hours, the error in the ensemble-mean 10-m wind speed is approximately 14 m s\(^{-1}\), compared to approximately 18 m s\(^{-1}\) for the WRF-GFS forecasts (Fig. 6b). Unlike WRF EnKF analyses, the TC structure is poorly represented in the WRF-GFS initial conditions and the vortex must spin up during the first few hours of the simulation; this issue will be further explored in the next section. At short lead times (<18 h), the official NHC forecast has smaller errors as compared to the EnKF; beyond that, the WRF EnKF errors are roughly 7 m s\(^{-1}\) smaller. We note that the large intensity errors in GFS forecasts partially result from the coarse horizontal resolution of the available model output (1° latitude and longitude).

Although the dropsonde data has only a small effect on 6-h TC forecasts, it is possible that the impact of this data could become greater at longer lead times. To test this possibility, 48-h forecasts initialized from the no drop analysis ensemble are compared to the control forecasts. At all forecast lead times, the track and intensity forecast errors for the no drop ensemble are within 5% of the control ensemble forecast, indicating that for longer lead times, the dropsonde data has minimal effect on the TC forecast. Although other studies have shown positive impact of dropsonde data over many cases (e.g., Aberson 2003; Wu et al. 2007; Aberson 2008), there are individual storms for which the dropsonde data have minimal impact or lead to degraded forecasts.

4. Inner domain results

Assimilation on the inner domain also produces analysis ensembles that capture well the track and, to a lesser extent, the intensity of Katrina. The RMS error in the TC position is slightly larger than the horizontal grid spacing (Table 1). In contrast to the minimum SLP estimates on the outer domain, the TC minimum SLP for the inner domain analyses are generally too low. While

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3 Differences can arise in individual members because of the lateral boundary condition perturbations.
it may appear that the outer domain has smaller minimum SLP errors, the RMS outer domain analysis SLP errors are 1.5 hPa higher during the time period covered by the inner domain. The largest errors occur around 0600 UTC 28 August, because the TC undergoes rapid intensification 12 h earlier than NHC advisory estimates. For maximum wind speed, the errors are smaller than the outer domain; however, these values are typically less than the best-track estimate. Assimilating dropsonde data within the TC is important on this domain. The RMS error in the ensemble-mean background forecast of TC position and minimum SLP are 20% and 70% larger, respectively, when dropsonde data is not assimilated (no drop case in Table 1). We note that TC position assimilation is needed on this domain because information from the outer domain is communicated to the inner domain only through lateral boundary conditions.

Even though data assimilation is performed independently on each domain, analysis increments on the inner domain show a similar dipole pattern to that obtained on the outer domain (Figs. 3c,d). Assimilating the dropsonde wind observation northwest of the TC shifts the storm to the southeast in both SLP and 500-hPa zonal wind. The leading two EOFs of the SLP analysis increments on this domain exhibit dipoles centered on the TC and explain 25% and 20%, respectively, of the variance (Fig. 4d). The third EOF (Fig. 4e) explains 9% of the variance and is mainly related to intensity, as is the case for the outer domain. For 500-hPa zonal wind, the leading EOF is a north–south-oriented tripole centered on the TC, explains 17% of the variance, and is associated with north–south displacements in the TC (Fig. 4f). The second (13% of variance) and third (6% of variance) 500-hPa zonal wind EOFs are related to east–west displacements and intensity, respectively (not shown).

Recall that covariance inflation is not applied on this domain because it amplifies asymmetric increments to the TC, which distort its structure. To demonstrate how data assimilation affects the TC structure, Fig. 8 shows the ensemble-averaged azimuthal Fourier amplitude spectrum of SLP, 850-hPa temperature, and 850-hPa tangential wind at a radius of 100 km from the TC center before and after data assimilation at 1800 UTC 27 August. This time coincides with an intensive observing period for the RAINEX project, with many dropsondes available for assimilation within the TC; other times show qualitatively similar results. The spectra show a peak at azimuthal wavenumber 1 with a steep decline toward higher wavenumbers. With few exceptions, the analysis amplitude is larger at nearly all wavenumbers, but especially at higher wavenumbers, which suggests that data assimilation renders the storm more asymmetric. Conversely, these results also suggest that the storm becomes more axisymmetric during the 6-h forecast. The enhanced asymmetric structure in the analysis could result from a number of factors, including variance in storm position, sampling error due to using a small ensemble, and differences in the location and amplitude of convection in each ensemble member.

Although EnKF data assimilation introduces asymmetric noise to the TC structure, the analysis still retains

Note that because the TC location differs between ensemble members, the mean Fourier spectrum is not equal to the spectrum of the ensemble mean.
The horizontal distribution of precipitation for the forecasts initialized from inner domain analyses is broadly similar to the TRMM estimate (Fig. 9); however, the precipitation is 2.5 times higher in the eastern eyewall for the two forecasts that use EnKF initial conditions. The higher precipitation rate and associated latent heating in the WRF simulations is consistent with the WRF simulations of Zheng and Chen (2006) and may explain the persistent low bias in the model’s TC minimum central pressure. Furthermore, the EnKF forecast shows a primary rainband that is narrower and displaced north relative to the TRMM estimate.

It is difficult to distinguish between the full field and cold start precipitation distributions (Figs. 9a,b). This result seems to indicate that having analyzed microphysical fields has little bearing on short-term precipitation forecasts; the model is able to spin up the appropriate cloud fields in a short amount of time. Nascimento and Droegemeier (2006) reached a similar conclusion for mesoscale convective systems by showing that setting the initial vertical motion field to zero had minimal affect on the forecast. In contrast, the precipitation distribution for the GFS field forecast, which is initialized from a nearly symmetric vortex, is broader than either the full field or cold start forecasts (Fig. 9d). This result suggests that high-resolution analyses produced by an EnKF system can lead to more realistic short-term forecasts of microphysical fields than those from coarser operational analyses.

The previous result suggests that WRF EnKF-initialized forecasts may suffer from fewer spinup problems during the first few hours of a forecast as compared to using an analysis from a different model. Another measure of the quality of the initial conditions is given by the amount of imbalance (acoustic and gravity wave activity) in the model. To assess this measure we evaluate the RMS value of the time derivative of the dry air mass field at each grid point within 600 km of the TC center at 2-min intervals for forecasts initialized from an EnKF analysis and from the GFS analysis. Figure 10 shows that this quantity is initially large for both forecasts and decreases to an equilibrium value over approximately 2–3 h; however, the EnKF-initialized forecast is always less than or equal to the GFS-initialized forecast and equilibrates at an earlier forecast hour, which is similar to the results obtained by Chen and Snyder (2006). We note that this result also holds for the outer domain, which indicates that WRF TC forecasts initialized from EnKF analyses are less likely to have spinup problems than forecasts initialized from another model’s analysis. Furthermore, this calculation also indicates that although
Data assimilation introduces high-wavenumber noise into the TC, this noise appears to have relatively little impact on the balanced fields after about 1 h.

5. Discussion and conclusions

Ensemble analyses and forecasts of Hurricane Katrina are generated on a nested domain using an ensemble Kalman filter based on the WRF model. Conventional in situ observations, reconnaissance dropsondes, and NHC position data are assimilated every 6 h for the duration of Katrina’s lifetime. These experiments show that the EnKF approach performs well for TC data assimilation without employing special schemes such as vortex bogusing and repositioning. Although this method performed well for a single storm, further research with additional cases is needed to assess the generality of the results.

Comparisons with NHC best-track estimates indicate that the EnKF analysis and forecast ensembles on both domains provide accurate estimates of the TC position, and to a lesser extent, the TC intensity. On the outer domain, assimilating position data leads to lower analysis errors as compared to the background forecast, though the same is not true for intensity. In contrast, when position observations are withheld, the position and intensity errors are significantly larger. Data denial experiments indicate that dropsondes that sample the synoptic environment provide minimal benefit to the outer domain; however, dropsondes deployed within the TC lead to significant reductions to the position and intensity errors on the inner domain. Horizontal distributions of precipitation on the inner domain compare qualitatively well with TRMM satellite estimates, except that the model produces twice as much precipitation as the satellite value. This favorable comparison is attributed to having initial conditions that contain a dynamically consistent three-dimensional representation of the TC, rather than properly analyzed microphysical fields (cf. Figs. 9a,b).
Ensemble forecasts initialized from the WRF EnKF analyses have smaller errors for TC track and intensity compared to GFS forecasts, WRF forecasts on the same domain that are initialized from GFS analyses, and the official NHC forecast. Smaller track and intensity errors indicate that the WRF EnKF analyses provide a better estimate of the steering flow and a TC structure that is more compatible with the model, respectively.

WRF forecasts initialized from EnKF analyses have a shorter spinup time and contain less initial imbalance as compared to simulations that use initial conditions from the GFS model. As a consequence, high-resolution TC forecasts initialized from an EnKF analysis are less likely to suffer from large convective bursts that may occur during the first 6 h (e.g., Davis et al. 2008). If large enough, these convective bursts can significantly alter the TC short-term structure, which in turn, can limit the usefulness of longer-term forecasts (C. Davis, NCAR, 2008, personal communication).

Analysis increments for observations near the TC tend primarily to shift the position of the storm. Excessive variance in the TC position also produces asymmetric analysis increments, which can erroneously affect the intensity of the storm and introduce asymmetric structural noise. These asymmetries distort the TC in the analysis, and often lead to a weakening of the TC through axisymmetrization during the first few hours. Assimilating observations before this symmetrization is complete may potentially contribute even more high-wavenumber noise, which would result in larger short-term intensity forecast errors. This problem of excessive TC position variance can be partially overcome by assimilating TC position at high temporal frequency, thereby decreasing position variance.

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