Advanced Data Assimilation for Cloud-Resolving Hurricane Initialization and Prediction

Data assimilation aims to decrease errors in initial conditions of numerical weather prediction models, which are a primary source of uncertainty in hurricane prediction. This study examines the performance of three advanced techniques that assimilate inner-core, high-resolution Doppler radar observations for cloud-resolving hurricane initialization and forecasting for Hurricane Katrina.

Hurricanes are among the costliest and deadliest natural disasters, and accurately forecasting them at all scales depends critically on various hurricane numerical weather prediction (NWP) models. Forecast uncertainties can come from inaccuracies in the forecast model, errors in the initial conditions, and the especially chaotic nature of weather systems when moist convection is present. An essential component of all NWP systems is data assimilation, which combines all available information sources (from both the model and observations) to produce the most-accurate possible description of the flow state (initial conditions) and the errors resulting from uncertainties in the various information sources.[1]

Variational data assimilation approaches find the best estimate of the initial state by minimizing a scalar cost function consisting of the distance between a background state vector (usually a prior forecast normalized by the background error covariance) and an observation state vector normalized by the observational error covariance.

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In this article, we compare the performance of several advanced data assimilation approaches for Hurricane Katrina. The weather research and forecasting (WRF) variational data assimilation system (WRF-Var) we used in this study was developed based on the dynamical core of advanced research WRF[2] (ARW) via multivariate incremental formulation,[3] including both 3DVar and 4DVar algorithms. WRF 3DVar was adapted from the MM5 3DVar system,[4] and the WRF 4DVar[5] algorithm was recently released to extend WRF 3DVar, with the additional capability of dealing with asynoptic data with implicit flow-dependant forecast uncertainties.

The Target Algorithms

Mathematically, the WRF-Var or any other variational method aims to obtain a balanced state analysis subjective to both dynamic and statistical constraints by minimizing a cost function J:

$$J = J_b + J_o + J_c = \frac{1}{2}(x_0 - x^b)^T B^{-1}(x_0 - x^b) + \frac{1}{2}\sum_{k=0}^{K}\left[H(x_k) - y_k^o\right]^T O^{-1}\left[H(x_k) - y_k^o\right] + J_c$$

where J_b, J_o, and J_c are the background, observation, and penalty, respectively, and k denotes an analysis time during the assimilation window.

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In the background term J_b, x_0 is the analysis at the initial time, x^b is the first guess, and B is the background error covariance. In the observation term J_o, H is an observation operator, O is the observation error covariance, and x_k and y_k^0 are the analysis and observations states distributed at time k during the assimilation window. In J_c, a digital filter is introduced to remove high-frequency waves in the analysis state. The fundamental difference between 4DVar and 3DVar is that the 4DVar usually minimizes the cost function J over different times (using an adjoint model), while the 3DVar has only $k = 0$ at one fixed time.

The background error covariance controls the distribution of observational information in space and between physical variables and is assumed to be largely isotropic in space and invariant in time. In WRF-Var—or any other variational scheme—is typically derived from

- forecast error statistics calculated on the basis of forecast differences with varying lead times over a period of at least one month or
- an ensemble forecast constrained by hydrostatic and geostrophic balances.

The ensemble Kalman filter (EnKF) is an alternative data assimilation method first proposed for geophysical applications by Geir Evensen.[6] It's based on the original linear, recursive Kalman filter that produces the unbiased minimum variance estimate, in a least-square sense, under the assumption of unbiased noise processes. Unlike 3DVar, it uses ensemble forecasts to estimate flow-dependent background error covariance. As in the standard Kalman filter, the update equation can be formulated as $x^a = x^f + \mathrm{K}(\mathrm{y} - Hx^f)$, where x^f represents the prior estimate or first guess, x^a is the posterior estimate or analysis, y is the observation vector, H is the observation operator that returns observed variables given the state, and K is the Kalman gain matrix defined as $K + P^f H^T (HP^f H^T + R)^{-1}$ where P^f and R represent the background and observational error covariance, respectively. In EnKF, the flow-dependent P^f is estimated through an ensemble of short-range forecasts. Observations are taken sequentially with the assumption of uncorrelated observation errors. Chris Snyder and Fuqing Zhang first applied EnKF to assimilate Doppler radar observation.[7] In our study, we used Z09, the WRF-based regional-scale EnKF system we developed to assimilate high-resolution Doppler radar observations for initializing cloud-resolving tropical cyclone (TC) prediction.[8,9]

EnKF is equivalent to variational methods for linear systems with Gaussian error distributions and an infinite ensemble size. However, it offers significant advantages over variational methods. It uses short-term ensemble forecasts to estimate more realistic, flow-dependent forecast (background) error covariance that doesn't rely on prespecified physical balances. Such balances might not hold true for smaller scale systems with active moist convection. EnKF provides not only the best state estimation, it can also seamlessly couple the associated flow-dependent uncertainty with ensemble forecasting. Nevertheless, operational NWP centers around the globe continue to predominantly use variational data assimilation techniques, although many have begun to incorporate flow dependencies in their background error estimates.

Currently, at the National Centers for Environmental Prediction (NCEP), two of the three operational hurricane prediction systems—the Global Forecast System (GFS) and the regional hurricane weather research and forecast (HWRF) model—are based on the newly developed gridpoint statistical interpolation (GSI) analysis, which is one form of the 3DVar method.[10] Each of these prediction systems uses some form of empirical vortex bogussing or relocation scheme for hurricane initialization that moves a forecasted TC from the previous cycle to the observed location in the first guess field before applying the GSI to assimilate various in situ and remotely sensed observations. The third hurricane prediction system, the Geophysical Fluid Dynamics Laboratory (GFDL) regional hurricane prediction model, directly inserts a symmetric, dynamically balanced initial vortex based on synthetic TC observations in the initial conditions directly before the forecast.

Hurricane Katrina

With more than 1,800 fatalities, Hurricane Katrina was among the five deadliest storms in US history; it was also the costliest, with an economic loss of more than US\$81 billion.[11] Katrina developed from a tropical depression and reached tropical storm strength around 1200 Universal Time Coordinated (UTC) 24 August 2005 just before making its first landfall on Florida's southeastern coast. The storm weakened slightly to a tropical storm after its first landfall but quickly regained hurricane intensity once it emerged over the southeast Gulf of Mexico. By 1200 UTC 28 August, it had intensified into to a Category 5 storm on the Saffir-Simpson hurricane scale.

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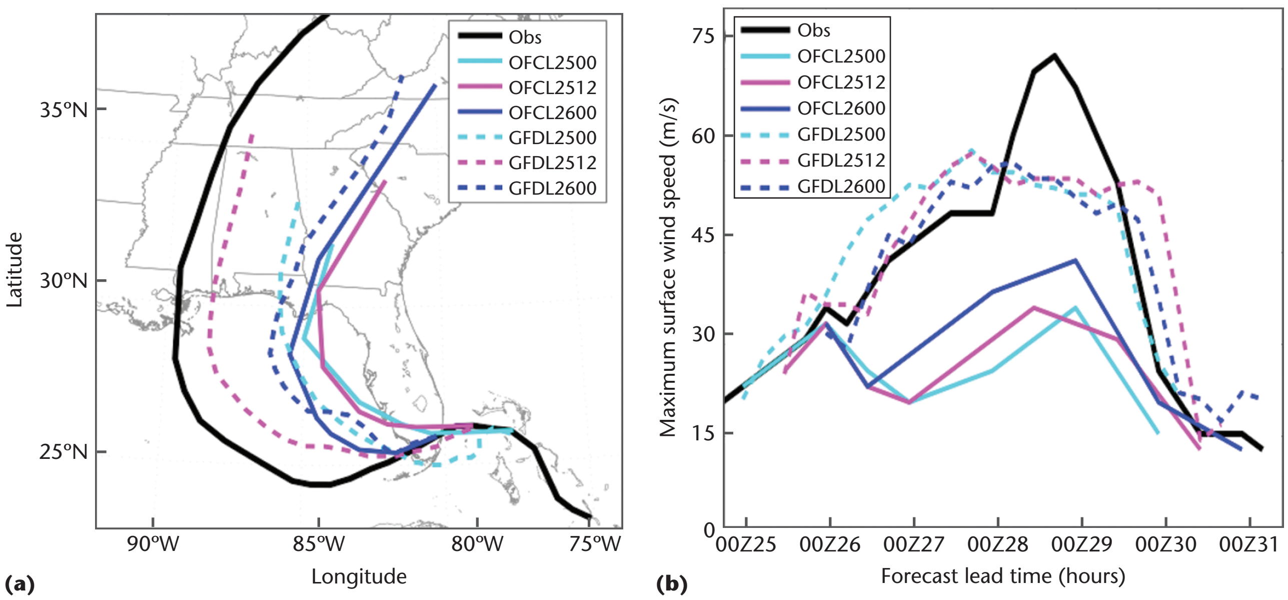

Figure 1. Hurricane Katrina's observed and simulated (a) track and (b) intensity. The US National Hurricane Center (NHC) best-track observations (Obs) are denoted in solid black; the NHC official operational forecast (OFCL) is shown in solid colored lines, and the Geophysical Fluid Dynamics Laboratory (GFDL) operational model forecast is shown in dashed colored lines. The NHC and GFDL forecasts were issued or initialized at 0000, 1200 UTC 25 and 0000 UTC 26 August 2005, respectively.

Katrina's intensity peaked at around 1800 UTC 28 August with maximum winds of 75 m/s^{-1} and a central pressure of 902 hectopascals (hPa), which is the fourth lowest ever recorded in an Atlantic TC.[11] Katrina made landfall in New Orleans on the morning of 29 August 2005 as it weakened into a Category 3 storm, inducing catastrophic flooding and extensive wind damage along the Louisiana and Mississippi coasts.

According to Richard D. Knabb and his colleagues,[11] the US National Hurricane Center (NHC) official track forecast 60 hours before the Louisiana landfall showed an average position error of less than half of the corresponding 10-year (1995 to 2004) average among all Atlantic basic hurricane forecasts.[11] However, operational (dynamic) hurricane prediction models and the subsequent NHC forecasts at longer lead times greater than 72 hours before Katrina's landfall in Louisiana were problematic, containing overwhelming large rightward biases.

The average of official intensity forecast errors over all lead times during Katrina was also considerably greater than the corresponding 10-year average. For example, Figure 1 shows large errors in track and intensity for both human-generated forecasts (the NHC official operational forecast, or OFCL), and operational dynamic model forecasts (the GFDL forecast). The difficulties in track and intensity forecasts by the operational models might come from deficiencies in the forecast model, the observations assimilated, or the data assimilation methods. For example, none of these operational models can explicitly resolving moist convection (such as in the eyewalls) and all lack the ability to ingest high-resolution cloud-scale observations such as those from ground-based or airborne Doppler radars, the impacts of which we'll examine here.

Assimilated Data and Experimental Design

Our assimilated high-resolution observations were radial velocity observations from a ground-based weather surveillance Doppler radar (WSR-88D) in Miami, Florida at approximately 1430, 1530, 1630, 1730, 1900, and 2000 UTC 25 August 2005. We selected these six volumes of ground-based radar observations to coincide with the approximate center times of a six-leg airborne Doppler mission conducted by a US National Oceanic and Atmospheric Administration (NOAA) P-3 reconnaissance aircraft for direct comparison of assimilating airborne versus ground-based Doppler observations.

Given the storm's close proximity to the Miami radar at these times, we were able to obtain large volumes of valid Doppler radial velocity. We used the same super-observation (SO) technique developed in Z09 to thin the massive radar observations, as well as for quality control. The total number of SOs at the six different times are 5,059,

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5,510, 6,012, 6,240, 10,126 and 6,575, respectively. We further randomly subsample these SOs at each time to produce data resolutions comparable to various model grid resolutions (that is, we use 1/18, 1/6, and 1/2 thinning ratios from the coarsest to the finest domains).

For analyses and forecasts, we used the WRF model version 3.1.1 with three two-way nested domains:

- the coarsest domain has 202 × 181 horizontal grids with 40.5 km grid space;
- the second domain has 181 × 160 horizontal grids with 13.5 km grid space; and
- the innermost domain has 253 × 253 grid points at a spacing of 4.5 km.

We interpolated the first-guess fields for all experiments from the NOAA operational GFS analysis at 0000 UTC 25 August 2005 and collected the lateral boundary conditions for the coarsest domain from the operational GFS forecasts. Starting at 0000 UTC 26 August, the second and the inner domains are automatically moved and centered on the storm's core using the vortex-following algorithm implemented in WRF. All model domains have 35 vertical layers, and the model top is 10 hPa. We also selected the same physical parameterization schemes for WRF as we used in Z09.

We generated the initial ensemble with 30 members for the WRF-EnKF with WRF-Var using the defaulted background error covariance option (cv3) at 0000 UTC 25 August. (See Z09 for more details on the EnKF system and the method for generating initial and lateral boundary perturbations.) We set the weighting coefficient α to 0.8 as in Z09 for relaxation covariance inflation; we also used the successive covariance localization (SCL) designed in Z09 in this study to effectively assimilate observations into all domains.

This study's 3DVar cycles are exactly the same as EnKF at each available observation time. We also assimilate the same observations over each domain. 4DVar contains two three-hour assimilation windows on the coarsest domain to assimilate the same 1/18 radar observations as those assimilated by EnKF and 3DVar on the coarsest domain to ensure that the data density is compatible to the grid resolution. For the background part of cost function J, we use ensemble forecasts valid at 1430 UTC 25 August 2005 to estimate B for both 3DVar and 4DVar experiments based on a preconditioning algorithm of control variable transform.[4] We tuned the variance and impact length-scale of background error covariance to obtain comparable results to EnKF, and thus avoid generating poor forecasts after radar assimilations.

We use the ensemble forecast mean valid at 1430 UTC as the prior estimate for all three assimilation experiments (EnKF, 3DVar, and 4DVar). Another experiment, named "NoDA," experiment directly initiated from the GFS analysis at 0000 UTC 25 August is integrated for 144 hours without assimilating radar or any other observations. All four experiments (NoDA, 3DVar, 4DVar, and EnKF) use the same planetary boundary conditions produced from the GFS forecast initialized at 0000 UTC 25 August 2005.

Radar Assimilation and Forecast Performance

Figure 2 shows the WRF simulated sea-level pressure (SLP) from all four experiments valid at 2100 UTC, one hour after each analysis. This time is selected for verification to assure the independence of the verifying observations and to let us adjust the respective analyses to the triply-nested model grids.

Hurricane Structure Simulations

Clearly, different assimilation techniques can result in large differences in the initial hurricane vortex's position, intensity, and structure compared to best-track and radar observations. More specifically, the minimum SLPs at this time from NoDA, 3DVar, 4DVar, and EnKF are 1,003, 1,002, 994, and 995 hPa, respectively. The 4DVar and EnKF experiments compare much more favorably than 3DVar and NoDA to the best-track SLP observation of 985 hPa at this one-hour forecast verification time. The center positions of the TC vortex (red circles in Figure 2) from EnKF and 4DVar are also much closer than those of 3DVar and NoDA to the best-track position (black dots). Despite similar minimum SLP, EnKF produces a much tighter low-pressure center that compares better with radar observations than that of 4DVar (see Figures 2c and 2d).

Figures 3 and 4 show the corresponding verifications of observed versus simulated radar reflectivity (composite) and Doppler radial velocity (projected to the lowest scanning elevation of the radar) at 2100 UTC. In terms of how well each algorithm depicts the initial TC structure, EnKF gives a much smaller initial vortex than 4DVar and 3DVar (Figures 3b and 3c), which is more consistent with radar observations (Figure 3a). EnKF also captures the asymmetry of the inner-core

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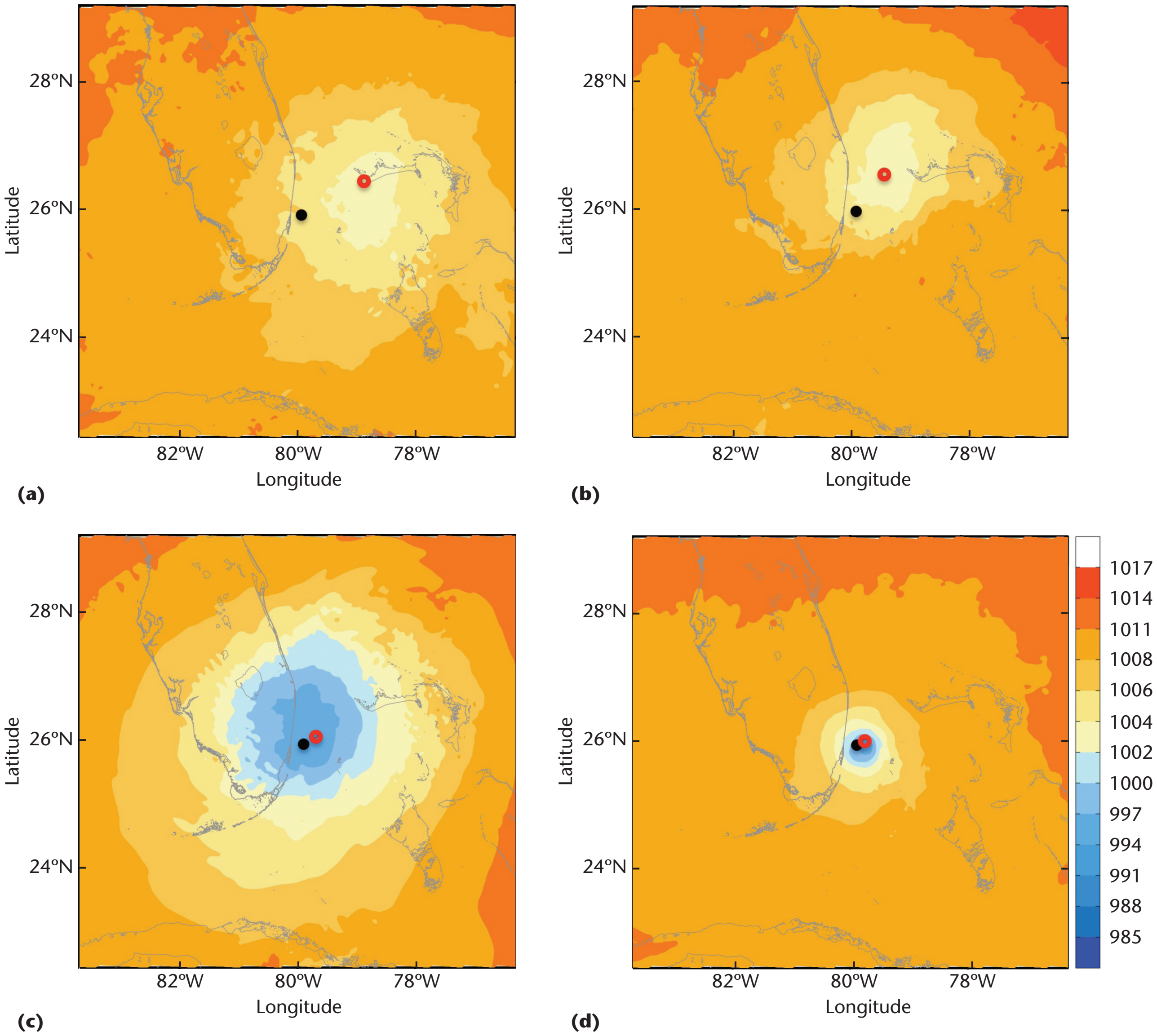

Figure 2. Simulated sea-level pressure. The simulations are valid at 2100 UTC 25 August and derived from four Weather Research and Forecasting (WRF) experiments: (a) WRF forecast without radar data assimilation (NoDA), (b) 3D variational data assimilation system (3DVar), (c) 4DVar, and (d) ensemble Kalman filter (EnKF). The black dots and red circles indicate the hurricane positions of the US National Hurricane Center's best-track simulated observations and prediction derived from the forecast, respectively.

vortex reasonably well, with strongest convection over the water, while 4DVar puts strongest convection over land.

On the other hand, the 3DVar produces a maximum in convection over the ocean, but with broad convective activity an no apparent eyewall structure. The simulated Doppler velocities from EnKF also verified better with observations than 4DVar, which outperforms 3DVar at this time (see Figure 4). Finally, the structure and size differences between the EnKF and 4DVar experiments persist more than 10 hours after the assimilation (not shown).

Track and Intensity Simulations

Figure 5 shows the ensuing track and intensity forecasts for all the experiments. Consistent with the analysis performance in Figures 2 through 4, the EnKF gives the best (and nearly perfect) 120-hour track and intensity forecasts despite a slight lag of approximately 6 hours for the time of landfall. The 4DVar gives track forecast comparable to the EnKF, but with considerably smaller maximum surface winds during the observed peak intensity period. The 3DVar and NoDA experiments give similar track and intensity forecasts throughout the integration; both are inferior to

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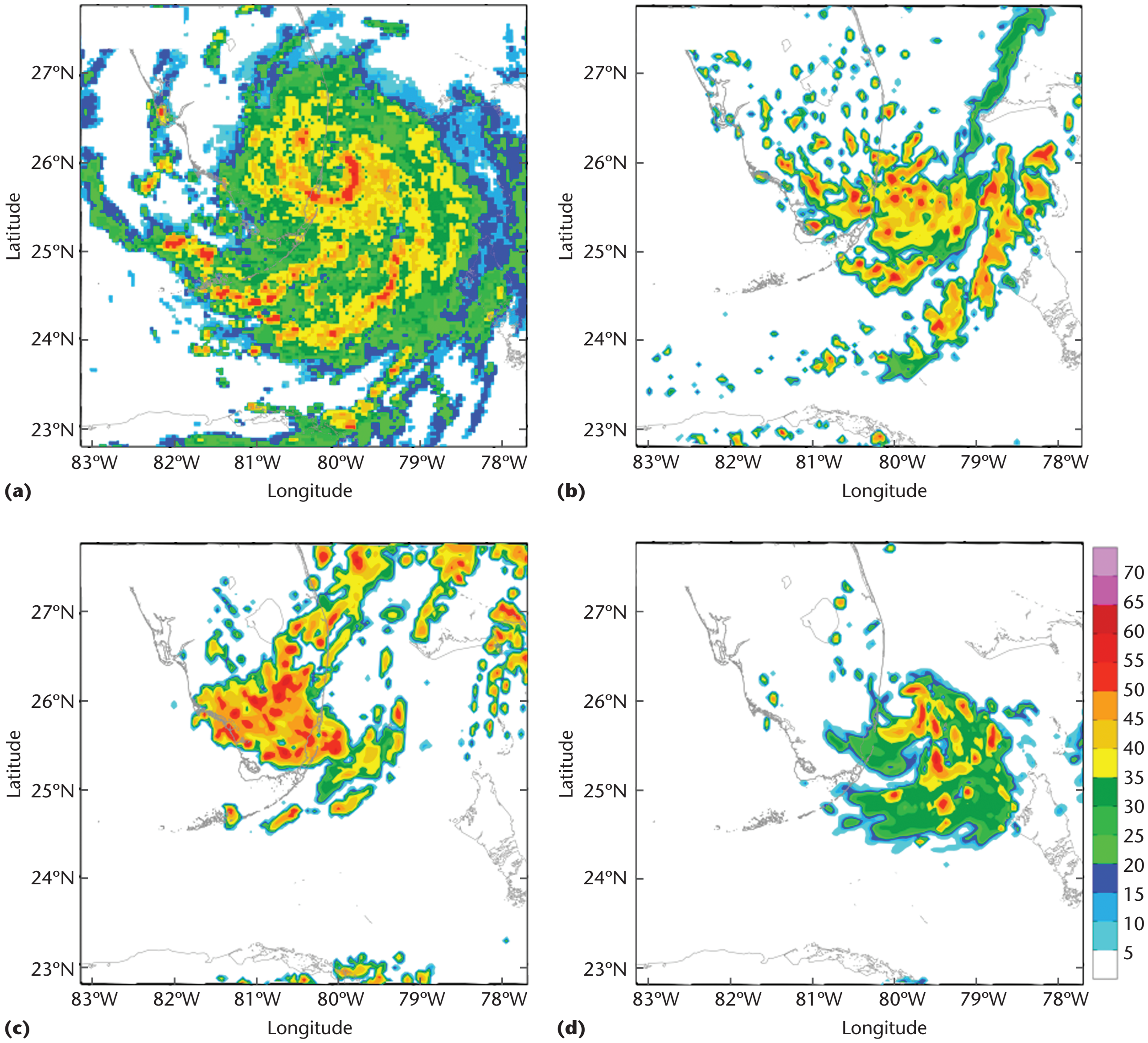

Figure 3. Observed versus simulated reflectivity. (a) Observed composite reflectivity of the Miami radar compared to the weather research and forecasting (WRF) simulated maximum radar reflectivity derived from the (b) 3D variational data assimilation system (3DVar), (c) 4DVar, and (d) ensemble Kalman filter (EnKF) valid at 2100 UTC, respectively. Here we also show the observed and simulated hurricane center positions, as in Figure 2.

EnKF and 4DVAR, but are generally better than the operational model and the official forecasts issued at 0000 UTC 25 and 26 August (see Figure 1).

Comparing the experiments immediately following the assimilation (2100 UTC 25 August) as well as with the subsequent 124-hour forecast shows the apparent advantages of more advanced data assimilation techniques (EnKF and 4DVar) over 3DVar. It also shows the benefits of assimilating high-resolution, convective-scale observations from Doppler radar (compared to NoDA).

The fundamental difference between the EnKF and 3DVar techniques is that EnKF estimates a flow-dependent background error covariance at each analysis through cycles of short-term ensemble forecasts, while 3DVar derives its mostly isotropic, static background covariance from one set of perturbations. The latter therefore relies heavily on assumed balanced constraints that might not be applicable for the TC vortex. The initial TC vortex's structure and size differences between the EnKF and 4DVar cases could also arise from differences in background error covariance and the assumption of geostrophically balanced flow, although the 4DVar assimilation is performed only on the coarsest grid with fewer SOs.

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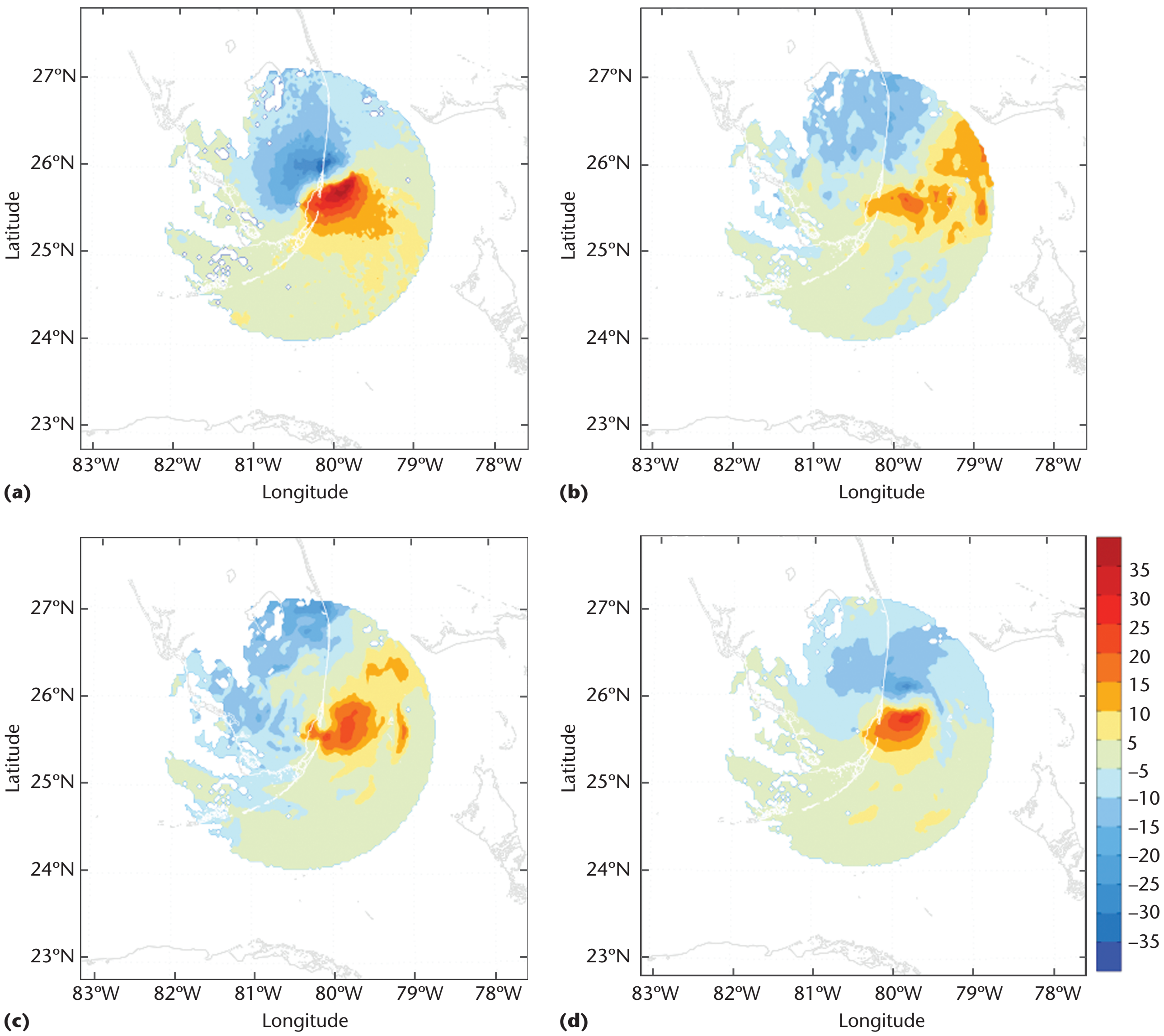

Figure 4. Observed versus simulated velocity. (a) Observed radar radial velocity on the lowest scanning elevation compared to (b) 3D variational data assimilation system (3DVar), (c) 4DVar, and (d) ensemble Kalman filter (EnKF) valid at 2100 UTC, respectively.

The current version of WRF 4DVar is computationally inefficient and not well parallelized; this limits our ability to run the 4DVar experiments at the same high resolution used by 3DVar and EnKF. Assimilating more SOs for 4DVar in the coarse domain (beyond the model grid's resolution) doesn't improve the 4DVar performance (not shown). But, as Figures 2 through 5 show, despite assimilating less data on a much coarser grid, 4DVar's advantages over 3DVar are clear. The 4DVar algorithm might partially alleviate the lack of flow dependence in its background error covariance through repeated cycles of forward and backward integrations by minimizing cost function. In this case, the 4DVar experiment performs considerably better than 3DVar in terms track and structure despite minimizing the cost function at a coarser resolution with less observations.

We carefully tuned the variance amplitude and covariance length scale used for generating background error covariance for both 3DVar and 4DVar. We did this to give the best performance when Doppler radar observations are assimilated. The EnKF algorithm is exactly the same as what was used in other storms and in real-time experiments. This further shows the need for flow-dependent background error covariance in the hurricane vortex initialization. EnKF's other advantage is its seamless coupling with ensemble

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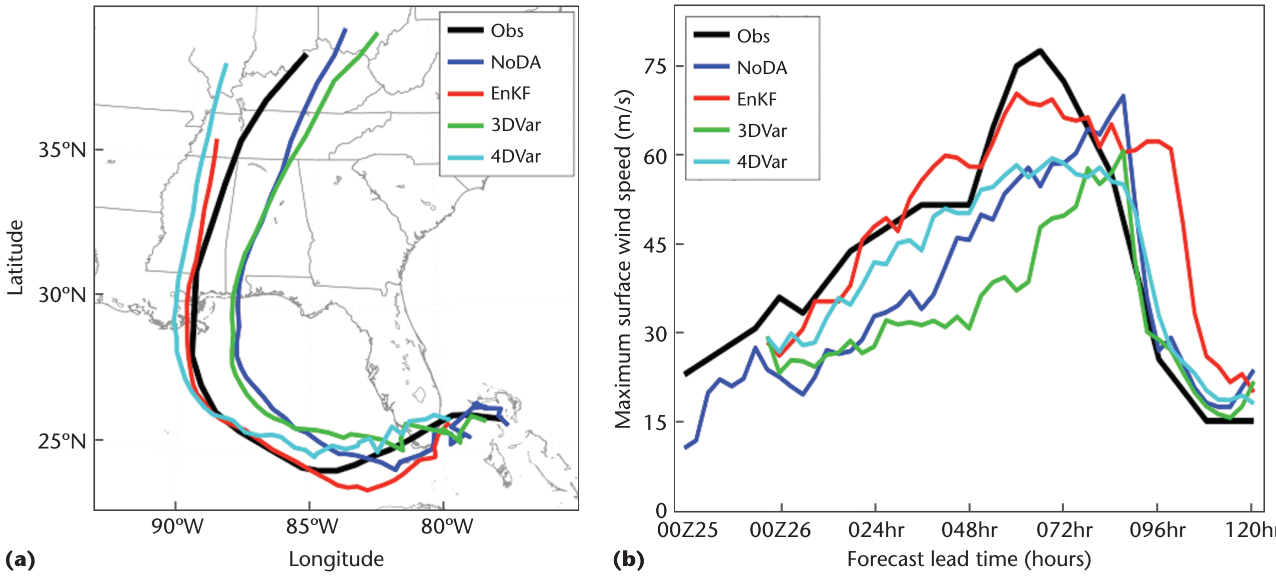

Figure 5. All experimental Hurricane Katrina forecasts. (a) The track and (b) intensity forecasts of experiments by weather research and forecasting (WRF) without radar data assimilation (NoDA), 3D variational data assimilation system (3DVar), 4DVar, and ensemble Kalman filter (EnKF).

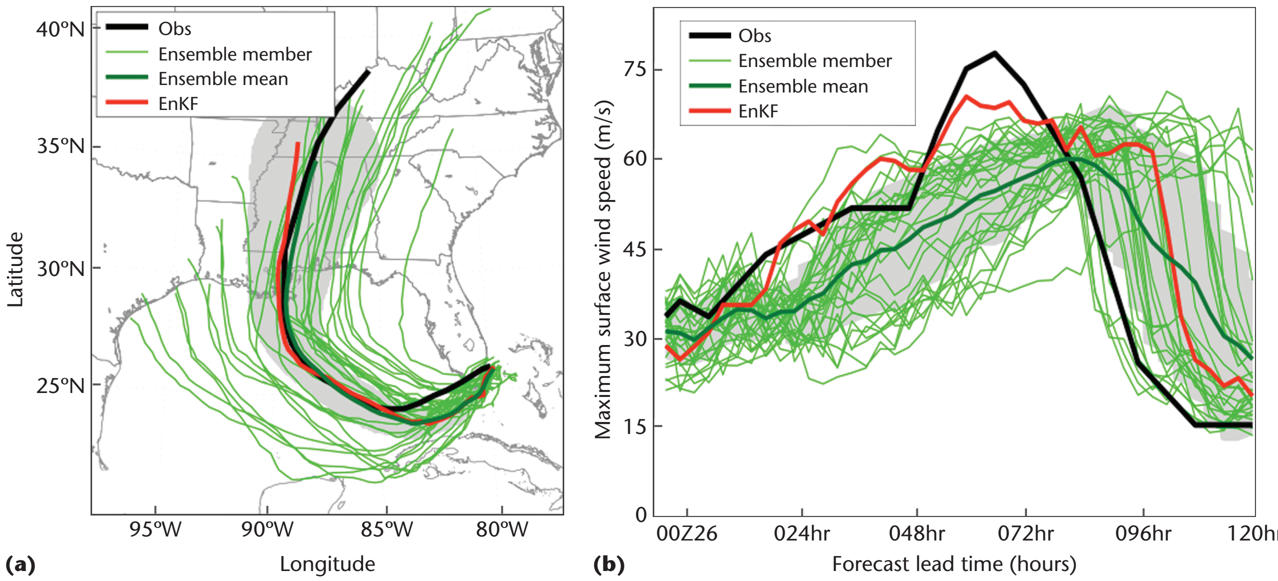

Figure 6. The 30-member ensemble forecasts. The (a) track forecasts (b) intensity forecasts were initialized with the ensemble Kalman filter (EnKF) perturbations at 2000 UTC 25 August. The thin green lines show individual member forecasts, the dark green line shows the average of the ensemble members, the red line shows the EnKF experiment (as in Figure 5), and the black line shows the US National Hurricane Center's best-track estimate. The thin shaded area indicates one standard deviation from the ensemble mean forecast.

forecasting systems; the flow-dependent analysis error covariance after assimilating observations provides ideal initial condition perturbations for the subsequent ensemble forecasts, in addition to the single deterministic forecasts from the mean EnKF analysis we described earlier.

Figure 6 shows the performance of the 30-member ensemble forecast initialized with the analysis perturbations from the EnKF experiment at 2000 UTC 25. The mean track forecast—averaged over all 30 ensemble members' positions and representing the ensemble's best estimate—also closely follows the best-track observations. The ensemble forecast further provides uncertainties associated with the ensemble mean estimate, indicated by the spread of the ensemble members. Large variations in the landfalling locations among different ensemble members partially

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reflect the difficulties in deterministic Katrina track prediction by NOAA operational forecast models and the NHC official forecasts before it moved into the Gulf of Mexico (Figure 1a).

That said, intensity forecasts by all ensemble members (and their mean) are significantly weaker than the deterministic forecast initialized from the EnKF mean analysis and the observations. The reasons for the ensemble's lower bias in the maximum surface wind forecasts compared to observations and to the deterministic forecast initialized with the mean EnKF analysis are unclear and require further investigation.

As our study shows, operational hurricane prediction systems struggled to produce adequate track and intensity forecasts with 96- to 120-hour lead times before Katrina's landfall, while the advanced data assimilation techniques—especially the EnKF implemented in the WRF model—demonstrate great promise in delivering more accurate forecast at these extended ranges. Moreover, ensemble forecasts initialized with the EnKF analysis perturbations might provide a realistic estimate of the event's forecast uncertainties. Our study also shows the clear advantage of using the 4DVar method over 3DVar, which is used in the current generation of US operational hurricane prediction models running at NCEP.

Because our results stem a single case study and ground-based Doppler observations are available only for tropical storms close to coastlines, additional research is needed to generalize our initialization techniques before transitioning to operational practice. The airborne Doppler radar systems might be an ideal alternative to the ground-based weather radars in providing high-resolution convective-scale observations. The NOAA airborne Doppler missions have provided routine surveillance of tropical storms in the Atlantic basin since 1982. However, they've never been used to provide data for operational numerical weather prediction systems.

There are several possible reasons for airborne radar observations being used only as iconographic products in TC operational forecasting:

- immature atmospheric data assimilation methods,
- communication speed between airplane and ground computer center is too slow for large radar data volumes,
- limited computer resources for cloud-resolving analysis and forecasting systems, and
- difficulties in airborne radar data processing and quality control.

The assimilation and data-thinning techniques we present here and in Z09, and based on ground-based Doppler radar radial velocity observations, make it possible to assimilate airborne Doppler observations. For example, with the support of the US National Science Foundation and the Texas Advanced Computing Center and in collaboration with NOAA under the Hurricane Forecast Improvement Project, Zhang and his colleagues presented a prototype future hurricane prediction system that performs cloud-resolving ensemble analysis and forecasting in massively parallelized, high-performance computing facilities by assimilating high-resolution airborne radar observations. Their efforts resulted in the first ever assimilation of airborne Doppler radar observations into hurricane prediction models. They used an ensemble data assimilation system and cloud-resolving ensemble forecasts for hurricanes in unprecedented real-time coordination, parallelization, and on-demand usage of more than 23,000 computer cluster cores simultaneously. We believe such work represents the trend of future hurricane prediction. CiSE

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