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Ensemble Assimilation of Nonconventional Observations for Nowcasting

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LONG-TERM GOALS

The ultimate goal of this project is to provide the US Navy with an increased capability of using storm observations from Doppler radars in the detection and prediction of hazardous weather events that affect the Navy operations, especially over oceans and in remote areas. By developing a high-resolution data assimilation capability that can effectively assimilate Doppler radar observations along with other conventional and remotely-sensed data, the US Navy will have the ability to analyze and forecast the battlespace atmospheric conditions with sufficient detail and accuracy for supporting the Navy mission in threat detection, weapons deployment, and weather safe operations.

OBJECTIVES

The objective of the study is to develop an advanced ensemble-based radar data assimilation system for the US Navy and to address some critical scientific and technique issues associated with radar data assimilation. The radar data assimilation system that will be developed will use flow-dependent background error covariance (instead of the static background error covariance) to account for the complexity and rapid change in the dynamical and microphysical structures inside and outside storms. The system will assimilate all the observed variables from different types of sensors, including Doppler radars, satellites, Unmanned Aerial Vehicles (UASs), and conventional meteorological observations, simultaneously to allow full interactions among the assimilated variables during the data assimilation to keep the balances among the dynamics, thermodynamics and microphysics in the model initial fields. The system will be able to use the observations from many types of radars on different platforms (WSR-88D, DoD meteorological radars and tactical radars both on-land and shipboard, etc.) with an appropriate quality control. Multi-scale data assimilation capability will also be one of the major features of the new radar data assimilation system that allows observational data at different scales to be assimilated concurrently to ensure the scale balance in the ensemble analyses.

APPROACH

The COAMPS-based ensemble Kalman filter (EnKF, Evensen 1994) recently developed at NRL (Zhao et al. 2013) will be the major tool for this study. All the radar data processing and quality control systems previously developed at NRL will be extended to cover the ensemble-based data assimilation and integrated into the EnKF for radar data decoding, pre-processing, quality control, bias removal,

and observational error estimation. The proposed ensemble radar data assimilation system will assimilate the raw Doppler radial velocity observations directly in the observational space. This will help to reduce the errors induced during the pre-retrieval and interpolation of wind vectors. A data thinning algorithm will also be developed for radar observations to reduce the data density (especially near the radar locations) and hence the data dependency before assimilation. In the last few years, NRL, NSSL and OU have jointly developed a data thinning algorithm for Doppler radial velocity. This algorithm will be further refined and used in the proposed ensemble radar data assimilation system. The NRL 3D Radar Mosaic will serve as the reflectivity data thinning algorithm.

The forward radar observation operators previously developed at NRL for the 3D/3.5D-Var (Xu et al. 1995, 2010; Zhao et al. 2006, 2008) will be adapted for estimating the radar observations in observational space from ensemble forecasts. For storm-scale data assimilation, one of the biggest challenges is the missing storms in the background fields so that there are no estimated radar observations available at observation locations for the data assimilation. The use of ensemble forecasts as the background should have some advantages over the use of a single deterministic forecast in this aspect. Appropriate ensemble spread that covers all the uncertainties of the model forecasts is critical.

Localization is a necessary step in all ensemble-based data assimilation systems to account for the insufficient ensemble size due to the lack of computational power. The length scale of the localization is a very sensitive parameter that affects the ensemble analyses. The assimilation of storm-scale data along with the large- and synoptic-scale observations makes this challenging issue even much more challenging. In this study, we will develop an observation-adaptive, variable-dependent, multi-scale localization algorithm. This algorithm will use a multiple-localization procedure and determine the localization scale based on observational data type, the control variable, and the statistics of the observational and background errors.

New algorithms will be developed that incorporate the dynamical and physical constraints from the variational methods into the EnKF to improve initial balance among the model fields and to reduce the spurious background error covariance outside observed storms caused by the zero/non-zero boundaries along the storm edges due to ensemble perturbations in storm location forecasts. The new hybrid technique will be built in the EnKF and should be computationally more efficient than the traditional hybrid data assimilation approach (that runs two systems in parallel), and is therefore more suitable for non-conventional, storm-scale sensor data assimilation.

WORK COMPLETED

FY15 was a successful year for radar data assimilation development at NRL. Major progress has been achieved both in the research and development of new and advanced radar data assimilation techniques and in the transition of the radar data assimilation system for Navy operations.

1. *Promotion of NRL 3DVAR radar reflectivity data assimilation for Navy operations*. By collaborating with the 6.4 COAMPS-OS® project (sponsored by PMW-120), the 3DVAR radar reflectivity data assimilation system, which includes the NRL radar data processing and quality control, the NRL 3D radar Mosaic, the COAMPS-OS Rapid Environment Assessment (REA) hourly data assimilation capability, 3DVAR radar data assimilation algorithm, storm forecast verification products, and a user interface, have successfully passed the operational test (OPTEST) conducted at the Fleet Numerical Meteorology and Oceanography Center (FNMOC) from 15 December 2014 through 1 April 2015. Results from the OPTEST show that radar

assimilation provides better spatial correlation with analyses and forecasted precipitation bands and cells, and results in higher forecast skill for lead times up to 12 hours. The system was promoted to operation on July 20, 2015. This is the first operational use of weather radar observations to improve the high-resolution analysis of storms in numerical weather prediction (NWP) for Navy operations, and COAMPS becomes one of few operational NWP models in the world that use radar observations in storm forecasts. This new capability is able to utilize radar data from both fixed land-based locations and ship-based platforms.

2. *Development and extensive test of NRL ensemble radar data assimilation system*. In the last year, several new and innovative radar data assimilation techniques and procedures developed at NRL were tested, improved, and integrated into the NRL ensemble radar data assimilation system. These techniques include:
    a. A new hybrid data assimilation algorithm that uses the variational method in the first loop to assimilate radar observations to adjust the ensemble mean of the background and to reduce bias, followed by an ensemble radar data assimilation in the second loop to update both the ensemble mean and perturbations of the model state variables for all ensemble members with flow-dependent background error covariance estimated from the ensemble forecasts. Unlike the traditional hybrid data assimilation method that runs two systems in parallel, this simplified approach incorporates the major components of the variational method into the EnKF and hence significantly reduces the computational cost, and therefore is suitable for radar data assimilation and rapid environment assessment.
    b. A time-expanded sampling (TES; Xu et al. 2008a, 2008b; Zhao et al. 2015) method that improves the effectiveness and efficiency of ensemble data assimilation and subsequent forecast with limited ensemble size. This approach samples a series of (preferably three) perturbed state vectors from each prediction run in an ensemble of forecasts at properly selected time levels in the vicinity of the analysis time. As all the sampled state vectors are used to construct the ensemble and compute the covariance (with localization), the number of required prediction runs and associated computation cost can be greatly reduced. If the sampling time interval is properly selected, the proposed approach can improve the ensemble spread and enrich the spread structures so that the filter can perform well even though the number of forecasts is greatly reduced.
    c. An ensemble rapid environment assessment (EREA) data assimilation procedure that assimilates radar observations and all other types of sensor data available into COAMPS with the EnKF to update the model fields every 3 hours followed by 6- or 12-hour ensemble forecasts. This procedure enables the application of ensemble analyses and forecasts in nowcasting.
    d. An algorithm and software that adds a new capability to the radar data assimilation system to use RAOB or other sounding data or COAMPS forecasts in the calculation of radar beam heights to replace the traditional method that uses the standard atmospheric refractivity conditions. This new capability improves the accuracy of the calculated radar observation height and hence the radar data assimilation.

    With these new techniques all integrated into the system, the ensemble radar data assimilation was extensively tested for a period of 5 days, from 23 June through 27 June 2005, with the model fields continuously updated by the assimilation of radar observations of reflectivity and Doppler radial velocity from 22 WSR-88D radars in the NEXRAD network over CONUS

along with other types of conventional and satellite meteorological data available. A control run was also conducted for the same period and with the same model setup except that radar observations were excluded. Results from the experiments show that radar data assimilation very significantly improves the model forecasts for all large-scale (45 km), mesoscale (15 km) and storm-scale (5 km) model grids with forecast lead time of up to 72 hours.

RESULTS

1. *Results from OPTEST*

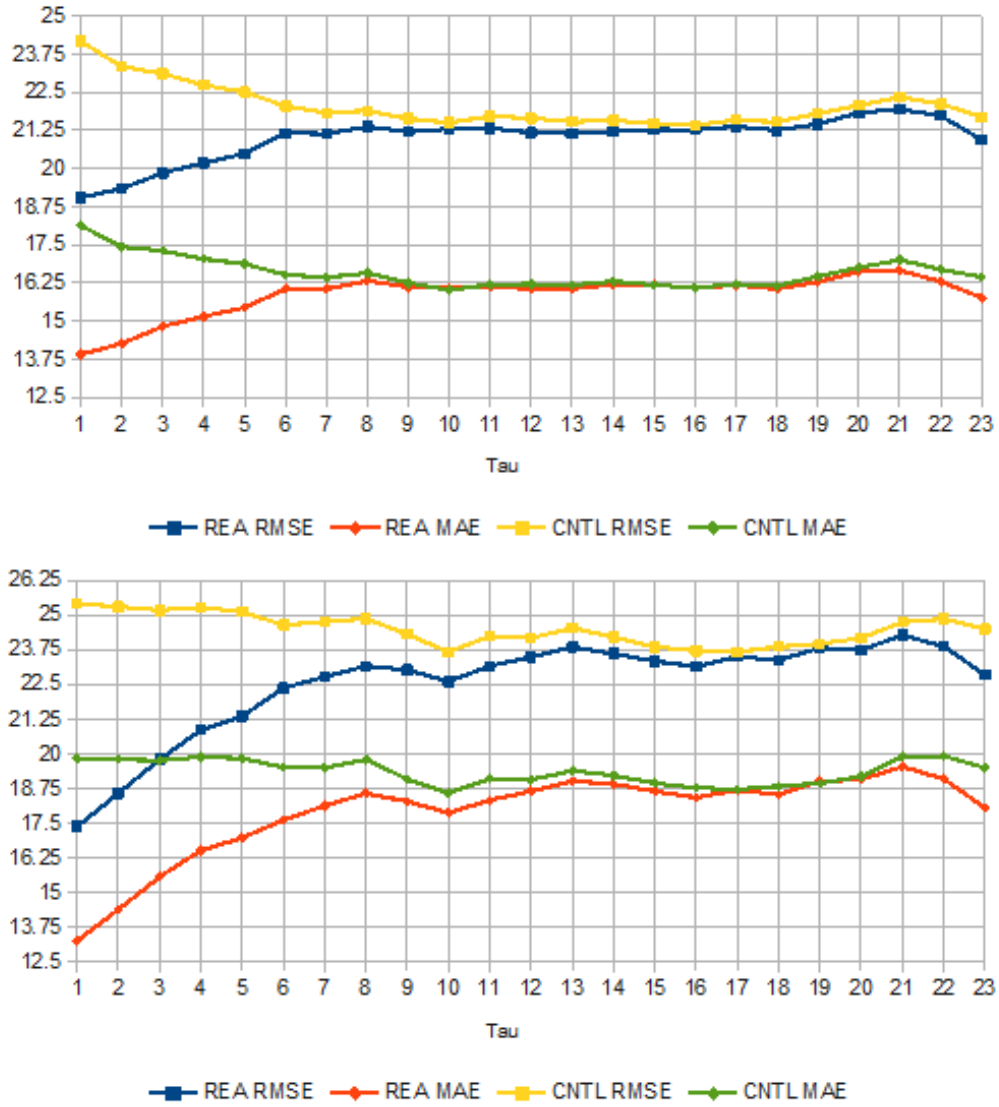

Figure 1. Root-mean-square-error (RMSE) and mean absolute error (MAE) scores in decibel units for the Virginia Capes 15 km grid (top) and 5 km grid (bottom), comparing radar data assimilation (REA) and the control run (CNTL, no radar). Tau is the forecast lead time in hours.

As mentioned earlier, the OPTEST for the COAMPS-OS with REA hourly radar data assimilation was running in real-time continuously for about 15 weeks at FNMOC in several areas over US coastal regions with real-time radar observations from the WSR-88D network. For comparison, the COAMPS-OS with exactly the same model setup but without radar data assimilation was also running in the same areas and for the same period used as the control (CNTL) experiment. Figures 1 shows the root-mean-square-error (RMSE) and mean-absolute-error (MAE) scores, as a function of forecast lead time (Tau), of the storm location and intensity forecasts (measured by radar reflectivity) from both the REA and CNTL experiments verified against radar observations over the 15-week OPTEST period. The top panel is for the 15-km grid and the bottom is for the 5-km grid of the VACAPES domain. Overall, REA performs better than the CNTL basically for the whole 1-day forecast period. But the significant improvement in storm prediction by radar data assimilation can be seen in about the first 8 hours of the model integration for the 15-km grid and about 12 hours for the 5-km grid. It also should be mentioned that both of the 8-hour and the 15-hour forecast lead times cover the lifetime of most mesoscale and convective-scale storms, which means that radar data assimilation can provide improved forecasts for the whole development of storms. To study the impact of radar data assimilation on the forecast of storms intensity, the RMSE scores for the VACAPES 5-km grid are calculated separately for the 15, 25, 35, and 40 dBZ bins, respectively. The results are given in Fig. 2. First of all, Fig. 2 shows that for all storm intensity categories, REA overall performs better than the CNTL. If we look at individual storm categories, we will find that the radar data assimilation has longer impact for storms with no or light precipitation. For the 15dBZ storms, for example, the impact lasts basically for the 1-day forecast period. During the first 6 hours of the model integration, however, it appears that the stronger the storms, the larger the radar data assimilation impacts. For the storms with the heaviest precipitation (40 dBZ), for example, radar data assimilation shows the largest reductions in the storm forecast errors. One possible explanation of the results in Fig. 2 is that for light and widespread precipitation, the storm last longer and does the radar data assimilation effect. For strong and isolated storms with heavy precipitation, on the other hand, the model forecasts are usually poor due to random nature of these storms. The radar data assimilation can greatly enhance the location and intensity of these storms in the forecasts and consequently significantly reduce the forecast errors. But those storms usually have shorter lifetimes. After the storms weaken and disappear, the data assimilation impact disappears.

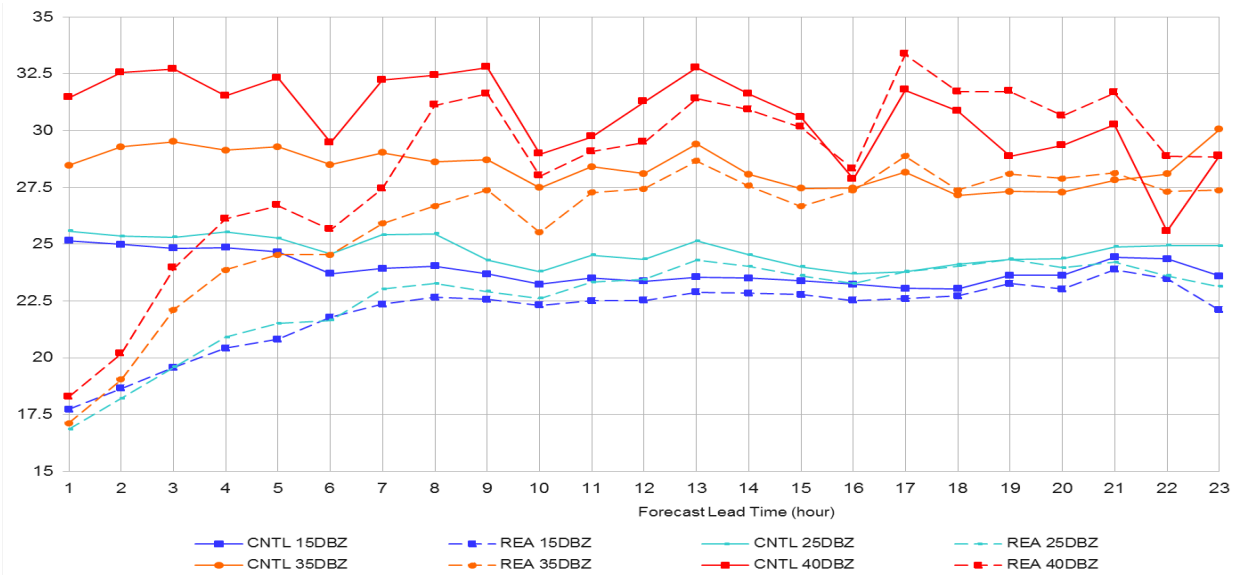

Figure 2. RMSE (in decibel units) for the Virginia Capes 5-km grid, comparing radar reflectivity strength (in dBZ) bins for radar data assimilation (REA) and the control run (CNTL, no radar).

2. Results from the extensive test of NRL ensemble radar data assimilation system

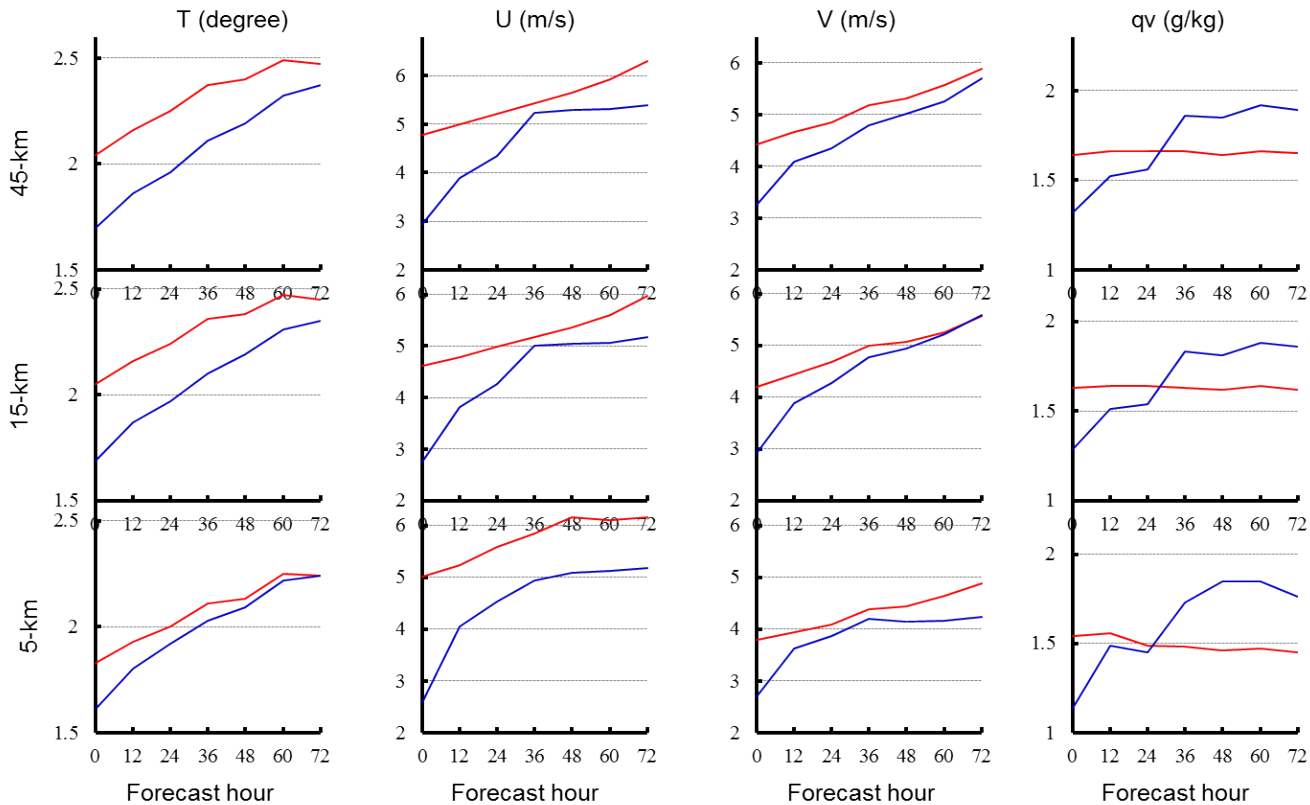

Figure 3. 5-day (23-27 June 2005) average RMSE of ensemble mean forecasts of T, u, v, and q_v, verified against RAOB sounding data every 12 hours, from Radar-DA (blue curves) and CNTL (red curves) experiments for COAMPS three nested grids.

The test of the NRL multiscale ensemble radar data assimilation system for the period of 23-27 June 2005 with several aforementioned new radar data assimilation techniques included also shows very encouraging results on improving the model forecasts. Figure 3 gives the 5-day average RMSE scores of the ensemble mean forecasts of temperature (T), horizontal winds (u, v), and water vapor mixing ratio (q_v) from both the radar data assimilation experiment (Radar-DA) and the control run (CNTL) for COAMPS three nested grids. These RMSE scores are from the verifications of the model forecasts against RAOB sounding observations over CONUS conducted every 12 hours during the 5-day experimental period. As it is seen in Fig. 3, radar data assimilation improves the forecasts of the model dynamic and thermodynamic fields throughout the 72-hour forecast period. Unlike most radar data assimilation studies that improve model forecasts only at the convective-scale, the NRL ensemble radar data assimilation system has the ability to assimilate radar observations into all model grids, ranging from large-scale to storm-scale, and as seen in Fig. 3, improves the model forecasts for all model grid resolutions. This demonstrates the success in the multiscale ensemble radar data assimilation that is enabled by the multiscale localization algorithm used by the EnKF for radar observations. The multiscale radar data assimilation improves not only forecasts of storms but also the prediction of the large-scale environment in which the storms develop. Also in Fig. 3, the largest improvements occur at τ=0, implying that the improved forecasts mainly result from the improved initial conditions from the assimilation of radar observations. For the moisture field, similar

improvements are also seen during about the first 24 hours of the model integration. After that, the radar data assimilation shows negative impact for all 3 model grids. It is not completely clear about what happens after 24 hours. But our previous study (Zhao et al. 2015) shows that the moisture field is usually dominated by mesoscale and storm-scale features and it changes rapidly with weather systems. Therefore, unlike the dynamic and thermodynamic fields, the model's memory about the moisture initial field is relatively short.

To demonstrate the impact of the continuously-cycled radar data assimilation procedures on model performance, Fig. 4 gives the RMSE differences of T, u, v, and q_v of the model analyses (τ=0) between CNTL and Radar-DA at each 12-hour cycle over the 5-day experimental period. This is for the 15-km grid. A positive value means reduction in RMSE and hence improvement in model analyses by radar data assimilation. Apparently, radar data assimilation reduces the analysis errors for all four model state variables. The most interesting thing in Fig. 4 is the increase of RMSE reduction of the analyses with the data assimilation cycles. The RMSE reduction for T, for example, is about 0.1 degrees at the beginning and about 6 times larger at the end of the experiment. This reflects the accumulated radar data assimilation impact through the continuous update cycles in which, the radar data assimilation improves the model's initial conditions and subsequent forecasts while the improved forecasts, in turn when used as background fields, improve the data assimilation.

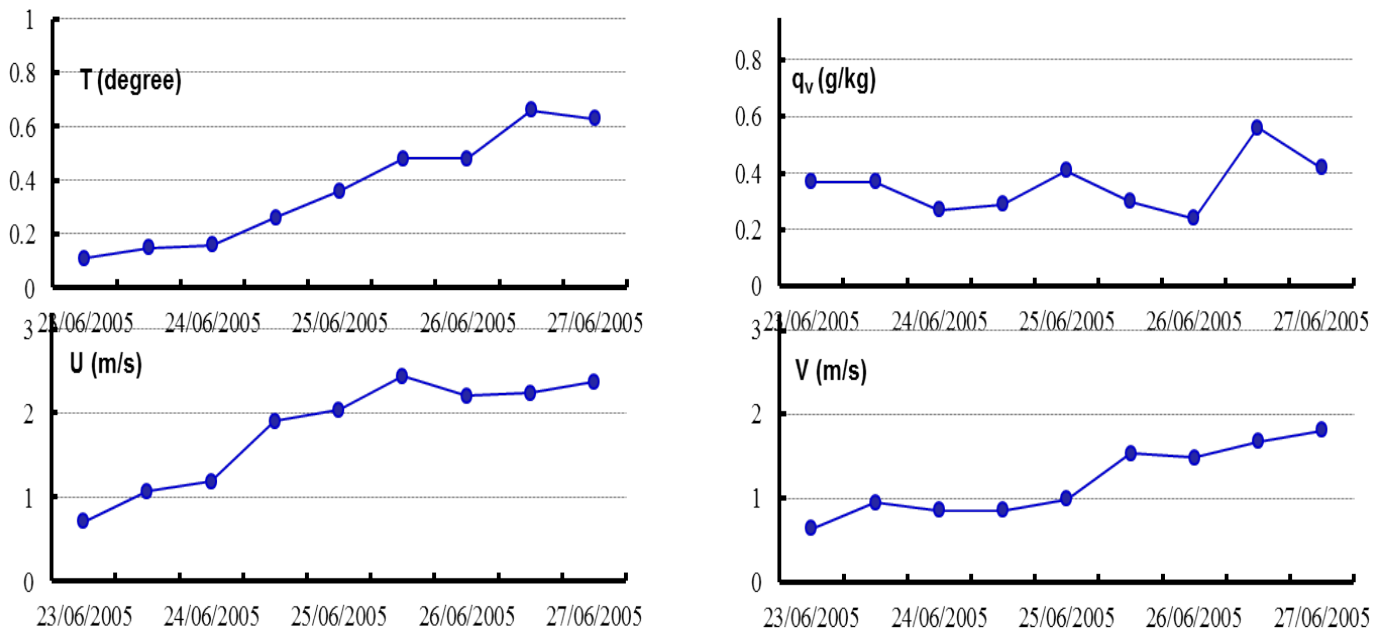

Figure 4. RMSE differences (CNTL – Radar-DA) for T, u, v, and qv of the model analyses (τ=0) calculated every 12 hours over the 5-day experimental period. A positive value means reduction in RMSE by radar data assimilation.

IMPACT/APPLICATIONS

The radar data assimilation systems developed at NRL will enable the US Navy to utilize the three-dimensional, high-resolution, frequently-observed storm information from shipboard tactical radars as well as from the land-based meteorological radars in coastal regions to early detect and accurately

predict high-impact weather events that affect Navy's operations and weapon systems. The 3DVAR radar reflectivity data assimilation system transitioned to FNMOC for operation has demonstrated its capability in assimilating the real-time storm observations from the shipboard SPS-48/HWDDC air defense radars for improving COAMPS-OS's capability and accuracy in storm forecasts over oceans. This adds new capability to the Navy in using nonconventional, through-the-sensor data to enhance the storm structure and intensity prediction. The ensemble radar data assimilation system recently developed at NRL with many advanced techniques included will significantly enhance the system's capability in maximizing storm information retrieval from radar observations and optimally using the storm information for rapid battlespace environment assessment.

TRANSITIONS

NRL 3DVAR radar reflectivity data assimilation system was transitioned to FNMOC, operationally tested, and promoted to operations on July 20, 2015.

RELATED PROJECTS

6.4-COAMPS-OS (PMW-120).

PUBLICATIONS

Zhao, Q., Q. Xu, Y. Jin, J. McLay, and C. Reynolds, 2015: Time-expanded sampling for ensemble-based data assimilation applied to conventional and satellite observations. *Wea. and Forecasting*, **30**, 855-872.

Skupniewicz, C., T. Neu, R. Lee, J. Cook, and P. Harasti, 2015: COAMPS-OS Real Time Environmental Assessment with HWDDC/NEXRAD Data Assimilation. *Operational Test Report*, unpublished, available upon request at FNMOC.

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