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Advances in Convection-Permitting Tropical Cyclone Analysis and Prediction through EnKF Assimilation of Reconnaissance Aircraft Observations

Yonghui WENG and Fuqing ZHANG

Department of Meteorology, and Center for Advanced Data Assimilation and Predictability Techniques, The Pennsylvania State University, Pennsylvania, USA

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Abstract

This article first presents an overview of the recent advances in the analysis and prediction of tropical cyclones through assimilating reconnaissance aircraft observations. Many of these advances have now been implemented in operational and experimental real-time hurricane prediction models. These advances are made possible through improved methodologies including more efficient quality control and data thinning, advanced data assimilation techniques that use ensembles to estimate flow-dependent error covariances, and improved numerical models running at convection-permitting resolutions, along with the availability of massively parallel computing.

Impacts of aircraft reconnaissance observations on hurricane prediction are then exemplified using a continuously cycling regional-scale convection-permitting analysis and forecast system based on the Weather Research and Forecasting (WRF) model and the ensemble Kalman filter (EnKF). In comparison to the non-reconnaissance experiment that assimilates only conventional observations, as well as to the WRF forecasts directly initialized with the global operational analysis, the cycling WRF-EnKF system with assimilation of aircraft flight-level and dropsonde observations can considerably reduce both the mean position and intensity forecast errors for lead times from day 1 to day 5 averaged over a large number of forecast samples including the real-time implementation during the 2013 Atlantic hurricane season. These findings reaffirm the added value and need for maintaining and maybe expanding routine airborne reconnaissance missions for better tropical cyclone monitoring and prediction.

Keywords EnKF; data assimilation; reconnaissance; tropical cyclone

1. Review of tropical cyclones prediction with aircraft reconnaissance observations

Since the Omega dropwindsondes (ODWs) were released from the NOAA WP-3D aircraft in 1982 that showed the potential for reducing the hurricane track forecast error (Burpee et al. 1984), the reconnaissance data has played an important role in hurricane analysis (Franklin et al. 2003) and forecasting (Aberson 2010).

Corresponding author: Fuqing Zhang, Department of Meteorology, and Center for Advanced Data Assimilation and Predictability Techniques, The Pennsylvania State University, University Park, PA 16802, USA
E-mail: fzhang@psu.edu
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Current routine reconnaissance missions in the Atlantic Basin include two WP-3D aircraft and one G-IV Gulfstream high-altitude jet operated by the United States National Oceanic and Atmospheric Administration (NOAA) and ten WC-130J aircraft operated by the United State Air Force Reserve (USAFR) 53rd Weather Reconnaissance Squadron (WRS), along with two experimental unmanned Global Hawk (GH) aircraft operated by the National Aeronautics and Space Administration (NASA). The

NOAA and USAFR aircraft may fly into most tropical cyclones reachable from the southeast coast of the United States, while the GH aircraft can reach close to the coast of Africa. These flights provide valuable flight-level, dropsonde, Doppler radar and/or stepped-frequency microwave radiometer (SFMR) observations. The dropsonde observations are transmitted in real time to the Global Telecommunication System (GTS) that can be used for operational hurricane analysis and forecasting.

Even though the dropsonde observations are available in GTS and the high-density observations (HDOB) of flight-level and SFMR winds are available in the National Hurricane Center (NHC) in real time, the inner-core reconnaissance observations are so far not routinely assimilated by the NOAA operational dynamical model[1]. The Global Forecast System (GFS) assimilates a limited amount of reconnaissance data outside of the storm and does not assimilate the inner-core observations except for the minimal sea level pressure in the Tropical Cyclone Vital Database (TCVitals), which contains the tropical cyclone (TC) location, intensity, horizontal wind, pressure, structure, and depth of convection, all of which are generated in real time every 6 h by forecasters (Trahan and Sparling 2012).

The NOAA high-resolution prediction includes two regional-scale dynamical models, one developed and maintained by the Geophysical Fluid Dynamics Laboratory (GFDL) (Bender et al. 2007) and the other is the Hurricane Weather Research and Forecasting (HWRF) model. The GFDL model initializes the tropical cyclones based on the GFS analysis but with a vortex bogus technique (Bender et al. 2007), while HWRF uses a hybrid ensemble and three-dimensional variational data assimilation analysis along with a vortex relocalization technique on the inner domain to initialize a TC (Bernardet et al. 2015).

Many research studies have shown promises in improving TC track forecasting by using reconnaissance data (e.g., Burpee et al. 1996; Franklin and DeMaria 1992; Tuleya and Lord 1997; Aberson and Franklin 1999; Aberson 2002, 2010), but the degree of improvement depends on the quality of the first guess that is usually interpolated from the global models (e.g., Chou et al. 2011; Weissmann et al. 2011). The improvement in TC intensity forecasts, on the other hand, is not always as conclusive as that seen in the track forecast (e.g., Tuleya and Lord 1997; Aberson 2002), which at least is partly due to the lack of sufficient model resolution.

The slower progress in improving the accuracy of hurricane intensity forecasting may also be due to the lack of sufficient and representative observations within the storm's inner-core area (Aberson 2008; Aberson et al. 2011) and/or due to the more limited predictability of the hurricane intensity changes (e.g., Sippel and Zhang 2008, 2010; van Sang et al. 2008; Zhang and Sippel 2009; Munsell et al. 2013, 2015; Zhang and Tao 2013; Tao and Zhang 2014, 2015).

Nevertheless, great promises in improving hurricane intensity forecasting have been demonstrated in recent years through the advanced assimilation of high-resolution inner-core observations into regional-scale convection-permitting numerical weather prediction models. For example, Zhang et al. (2009) demonstrated the potential of improving hurricane intensity prediction through assimilating high-resolution ground-based Doppler radar radial velocity with an ensemble Kalman filter (EnKF) based on the Weather Research and Forecasting (WRF) model. Weng and Zhang (2012) further enhanced the WRF-EnKF system with the capability of assimilating airborne Doppler radar on board the NOAA reconnaissance P3 aircraft.

Under the auspices of the NOAA Hurricane Forecast Improvement Project (HFIP; http://www.hfip.org), an experimental convection-permitting hurricane analysis and prediction system based on the WRF-EnKF system has been operated in real time since 2008 by The Pennsylvania State University for Atlantic tropical cyclones that assimilates airborne Doppler radar observations (Zhang et al. 2011). Averaged over all 102 applicable cases during 2008–2012 in real-time configurations, this experimental system is shown to be capable of reducing the day-1-to-day-5 hurricane intensity forecast errors by 15 %–43 % in comparison to the official forecasts of the National Hurricane Center (Zhang and Weng 2015). Similar or even more apparent improvement can be seen in this experimental system when compared to real-time operational forecasts by the two NOAA regional-scale dynamical hurricane models, HWRF and GFDL (Fig 1). All dynamical models including HWRF and GFDL are treated as a "late model" since forecasts from these models are only available to NHC forecasters considerably later than the model initialization time (a more detailed definition can be found at http://www.nhc.noaa.gov/modelsummary.shtml) and are thus interpolated to 6 h later. The homogeneous verifica-

[1]By the end of 2012 Atlantic hurricane season. The information is online available at http://www.nhc.noaa.gov/modelsummary.shtml.

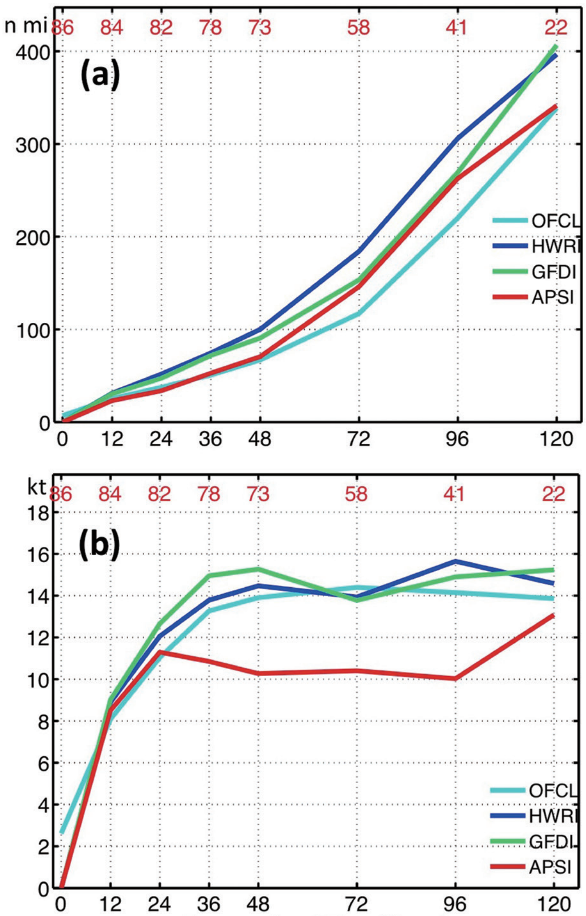

Fig. 1. (a) Mean absolute track (unit: n mi) and (b) intensity (unit: knot) forecast errors by homogeneous comparing among the PSU WRF-EnKF deterministic forecast (APSI, red), the NHC official (OFCL, cyan), and the current NHC regional dynamical models HWRF (HWRI, blue) and GFDL (GFDI, green). All dynamical models are treated as "late model" and interpolated to 6 h later. The track forecasts are directly shifted to the 6-h time-lagged forecasts, while the intensity forecasts use a 30-h interpolation method, which is used for late models in NHC. The interpolator process first applies a 1-2-1 smoother to an individual intensity forecast and then applies 30 h interpolation with 6-h time lag to the forecast based on when the model guidance is available. The interpolator applies the full adjustment to the time-lagged forecast out to 18 h, applies a linearly decreasing adjustment from 18 to 30 h, and then no adjustment for the remainder of the forecast. The numbers listed at the top of each panel are the sample size of the homogenized verification. The figure is adapted from Zhang and Weng (2015).

tion calculates the errors only when all forecasts are available at the same lead time for the same forecast cycle.

The rest of the article further extends the experimental hurricane analysis and prediction system of Weng and Zhang (2012) and Zhang and Weng (2015) to assimilate other aircraft reconnaissance data including flight-level data and dropsondes as well as standard GTS observations with a continuously cycling EnKF based on WRF. The following section first introduces the further enhanced cycling WRF-EnKF system along with the experiment design. Section 3 evaluates this enhanced system, and Section 4 discusses the impact of reconnaissance data assimilation. Concluding remarks are given in Section 5.

2. Further developed methodology and experimental design

2.1 Continuously cycling WRF-EnKF tropical cyclone analysis and forecast system

The convection-permitting hurricane analysis and prediction system used in this study builds upon the regional-scale WRF-EnKF system developed in Weng and Zhang (2012) but with the addition of a continuously cycling capability and movable nests throughout the life cycle of a tropical cyclone, along with using higher-resolution, improved physics and a larger number of ensemble members. The Advanced Research WRF (ARW) model (version 3.4.1; Skamarock et al. 2008) employed has three two-way-nested domains with 379 × 244 (D01), 304 × 304 (D02), and 304 × 304 (D03) horizontal grid points and horizontal grid spacing of 27, 9, and 3 km, respectively. D01 is fixed to cover the central to eastern three-quarters of the contiguous United States (CONUS) and tropical and subtropical north Atlantic, as shown in Fig. 2a. During the cycling analysis period, the two inner domains are movable following the TCVitals to ensure all ensemble members have the same analysis domains. For the WRF deterministic forecast after the EnKF analysis, the two inner domains are moving by following the tropical cyclone center with the WRF vortex-following technique. The WRF configurations and physics are the same as used in Zhang and Weng (2015).

To more systematically investigate the impact of aircraft reconnaissance data in the regional dynamical models, the key is to establish a baseline level of the skill and accuracy of the models run without any inner core reconnaissance data. Comparing to the operational forecast products (under homogeneous verification), the deterministic forecasts derived from

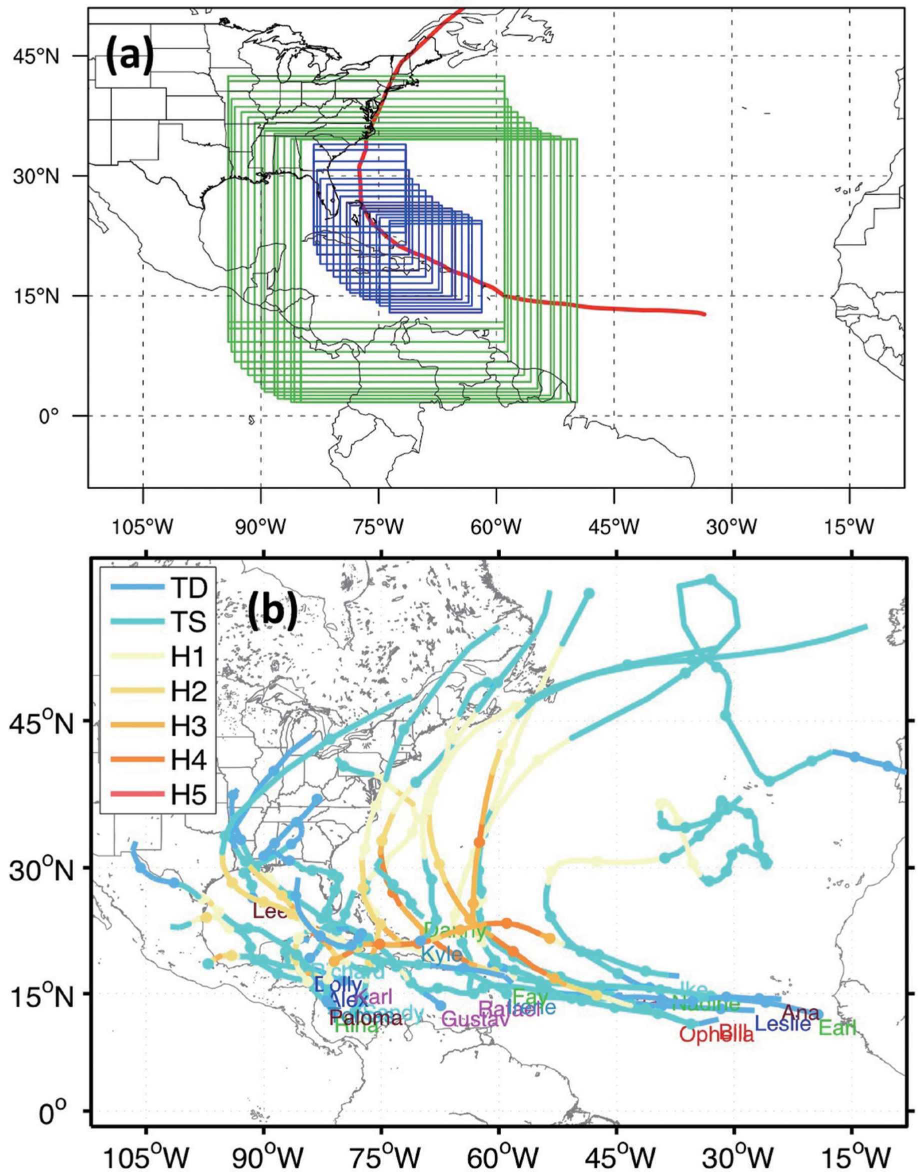

Fig. 2. (a) Example of movable domains of the cycling WRF-EnKF analysis system following TCVitals for Hurricane Irene (2011). The green/blue squares show the second/third domains every 6 h, and the red line is the track of Irene. (b) Atlantic storm tracks with recon missions during 2008–2012; the colors indicate the storm intensities.

the real-time Pennsylvania State University hurricane analysis and forecast system (designated as APSU by NHC) with the NOAA P-3 tail Doppler radars (TDR) is better than the official, operational HWRF, GFDL, and previous cycle GFDL (GHMI) and Decay Statistical Hurricane Intensity Prediction Scheme model (DSHP) for 24–120 h lead times, and it is also better than the GFS and Logistic Growth Equation Model (LGEM) within 96 h. (Since there is no vortex bogusing or intentional nudging toward best track estimates, the APSU does have a larger initial bias as found in earlier studies (Zhang et al. 2011; Zhang and Weng 2015). However, this comparison, though impressive, cannot differentiate the impacts of the inner-core radar data with the EnKF assimilation since the APSU system uses the operational analysis of NOAA's GFS as the initial analysis for the short-term ensemble before the WRF-EnKF analysis. The GFS analysis assimilates all route observations including satellite radiance. Since 2013, we have further extended the APSU system to a cycling WRF-EnKF analysis and prediction system capable of ingesting conventional data including surface and upper air observations and satellite-derived winds (but without satellite radiance assimilation) as benchmark control experiments for evaluating impacts of the reconnaissance data. Here is the specific design of the baseline EnKF experiment designed as CNTL.

1) Prior to the regional cycling EnKF analysis, the system is initialized with the operational GFS analysis when the tropical cyclone or an invest (low-pressure center of interest) appears to the west of 30°W in the north Atlantic and when NHC begins the official forecast (OFCL) or if the Climatology and Persistence Model (CLIPER5; Aberson 1998) starts forecasting products for this storm. The outer domain is fixed and is large enough to cover the central to eastern three-quarters of the CONUS and tropical and subtropical north Atlantic, while the two inner domains are centered with TCVitals (Fig. 2).
2) The initial and boundary conditions are perturbed with the same method described in Weng and Zhang (2012). The deterministic and 60-member WRF forecasts initialized with the GFS analysis and added ensemble perturbations are integrated for 12 h that serve as the prior fields for the cycling WRF-EnKF analysis system.
3) The WRF-EnKF analyses and forecasts assimilating the conventional observations are performed at a 3-h cycle, while the WRF deterministic forecasts are performed every 6 h with the EnKF analysis until the end of the storm or after the storm moves north of 45°N or east of 30°W. More specifically, the following steps are performed:
    a. During the cycling WRF-EnKF analysis, the same perturbing method described in step 2 is applied every 6 h to generate new perturbations, which will be used to blend with the WRF-EnKF 3-h ensemble forecasts to generate the new ensemble. The blending method implemented here is as follows: (i) The environmental fields 600 km outside of the TCVital center for the short-term WRF ensemble are replaced every 6 h with the available GFS operational analysis and newly generated perturbations valid at the same time. (ii) Fields between 300 and 600 km are blended with the short-term WRF ensemble and the new ensemble. (iii) The WRF-EnKF ensemble members are unchanged within the 300-km radius. Using the operational GFS analysis for the environmental fields and boundary conditions, we state the following: (i) The main objective of this study focuses on the impact of the data assimilation to the TC inner core. (ii) The GFS analysis assimilates all conventional observations, satellite radiance, and satellite-derived winds. (iii) The five-year retrospective run initialized with the GFS analysis shows that the hurricane track forecast with the WRF model is comparable in accuracy to the HWRF and GFDL hurricane models as well as OFCL (Zhang et al. 2014). (iv) Not assimilating environmental data is more computationally efficient in real time.
    b. The 3-h short-term deterministic WRF forecast initialized from the mean EnKF analysis (with the replaced environmental fields using the GFS analysis) is then used as the prior estimate to recenter the 60-member 3-h, short-term, prior ensemble before the next cycle EnKF analysis. In other words, the ensemble is regenerated every 3 h by combining the 3-h short-term deterministic WRF forecast and the 3-h ensemble forecast perturbations.
    c. All conventional observations including satellite derived winds from GTS within a 3-h window and within a 600-km radius around the storm center will be assimilated in all three domains with the EnKF; also assimilated will be the minimal sea level pressure in the corresponding TCVital file.
    d. After the first cycle of data assimilation, a 3-h deterministic forecast initialized with the EnKF analysis and an ensemble of 60-member 3-h forecasts using the perturbations are performed. The two inner nest domains of all ensemble members will follow the TCVital center with the preset moving technique in WRF.
    e. Also, after the first cycle of data assimilation, a 126-h deterministic forecast initialized with the EnKF analysis is performed as the control experiment.

Table 1. Reconnaissance cases for 2008–2012 Atlantic storms.

Year	Storm	CNTL MMDDHH-MMDDHH	ReCON MMDDHH-MMDDHH
2008	04-Dolly	072012-072418	072012-072418
	06-Fay	081400-082400	081400-082400
	07-GUSTAV	082512-090200	082512-090200
	09-Ike	090200-091312	090512-091312
	11-Kyle	092300-092812	092318-092812
	17-Paloma	110600-111000	110600-111000
2009	02-Ana	081200-081700	081612-081700
	03-Bill	081600-082312	081812-082312
	05-Danny	082612-082900	082612-082900
2010	01-Alex	062512-070112	062512-070112
	07-Earl	082600-090400	082712-090400
	13-Karl	091412-091800	091412-091800
	19-Richard	102012-102600	102012-102600
	21-Tomas	102912-110806	102912-110806
2011	09-Irene	082000-082900	082012-082900
	13-Lee	090200-090612	090200-090612
	16-Ophelia	092100-100218	092312-092900
	18-Rina	102212-102818	102312-102800
2012	09-Isaac	082000-083018	082112-082906
	12-Leslie	083000-091100	090712-090812
	14-Nadine	091000-100318	091118-100318*
	17-Rafael	101300-101718	101300-101718
	18-Sandy	102100-103018	102212-102918
Total	23 storms	758 cases	636 cases

*NASA Globe-Hawk dropsondes.

f. After the second cycle of the 3-h EnKF assimilation, the 3-h deterministic forecast initialized with the EnKF analysis and the 60-member 3-h ensemble forecasts initialized with the EnKF perturbations without the blend of the GFS analysis and without recentering will be forwarded to another assimilation cycle.
g. The following third cycle is then pushed to the GFS analysis episode, and the cycling system goes to step a to update the ensemble perturbations by blending the perturbed GFS. Steps a–f are then repeated until the end of the storm or until the storm moves north of 45°N or east of 30°W.

The experiment for assimilating reconnaissance data (named as ReCON) uses the same WRF-EnKF cycling analysis and prediction system as CNTL but with the additional assimilation of flight-level and dropsonde observations whenever available.

To avoid filter divergence due to either sampling or model error, we apply the covariance relaxation technique (Zhang et al. 2004; Eq. 5) with the relaxation coefficient α = 0.6. The covariance localization uses the Gaspari and Cohn (1999) fifth-order correlation function to cut off the influence of 30 grids in each domain. Also, the successive covariance localization method (Zhang et al. 2009) is applied to this study. Similar to Weng and Zhang (2012), the surface and flight-level observations and satellite-derived winds are randomly divided into three groups of 1/9, 2/9, and 6/9 (of the total available observations) with a horizontal localization radius of influence (ROI) of 405 km for all domains (group 1), 135 km for the two inner domains (group 2), and 45 km for the inner domain (group 3), respectively. For dropsondes, SCL is applied with different ROIs of 810, 270, and 90 km for each of the three domains, respectively. The minimal sea level pressure derived from TCVitals uses 1620, 540, and 180 km for each of the three domains, respectively.

2.2 Case selection

The retrospective cases selected in this study include all NOAA aircraft missions during 2008–2012, along with the Global Hawk experimental reconnaissance missions for Hurricane Nadine (2012) during the NASA field experiment HS3 (Braun et al. 2016). There are 23 storms (Fig. 2b) for a total of 758 cases for CNTL based on the 6-h forecast initialization cycles and a total of 636 cases for ReCON. The storms, and their start and end times for CNTL and ReCON, are listed in Table 1. All flight-level and dropsonde observations are available online at ftp://ftp.aoml.noaa.gov/hrd/pub/data/. The TCVitals data are available at ftp://ftp.nhc.noaa.gov/, while the GDAS and operational GFS forecasts can be obtained from https://rda.ucar.edu/.

The real-time cases selected in this study include all the 2013 Atlantic tropical cyclones (including the invest stages) for which the PSU experimental WRF-EnKF forecasts were delivered to the Tropical Cyclone Modeling Team (TCMT) in real time. These 125 cases are listed in Table 2. These real-time PSU WRF-EnKF forecasts can be found at ftp://ftp.nhc.noaa.gov/atcf/archive/2013 by searching the ID "APSU" in the NHC's operational A-deck files.

2.3 Verification

The forecasts will be verified against BEST from the Automatic Tropical Cyclone Forecast system (ATCF; Sampson and Schrader 2000). The maximum sustained 10-m wind speed (Vmax) of each TC is chosen to represent the TC intensity, although generally consistent performance is found using the minimum central sea level pressure (Pmin) as the intensity metric. The GFDL Vortex Tracker program (Gopalakrishnan et al. 2012) is applied to

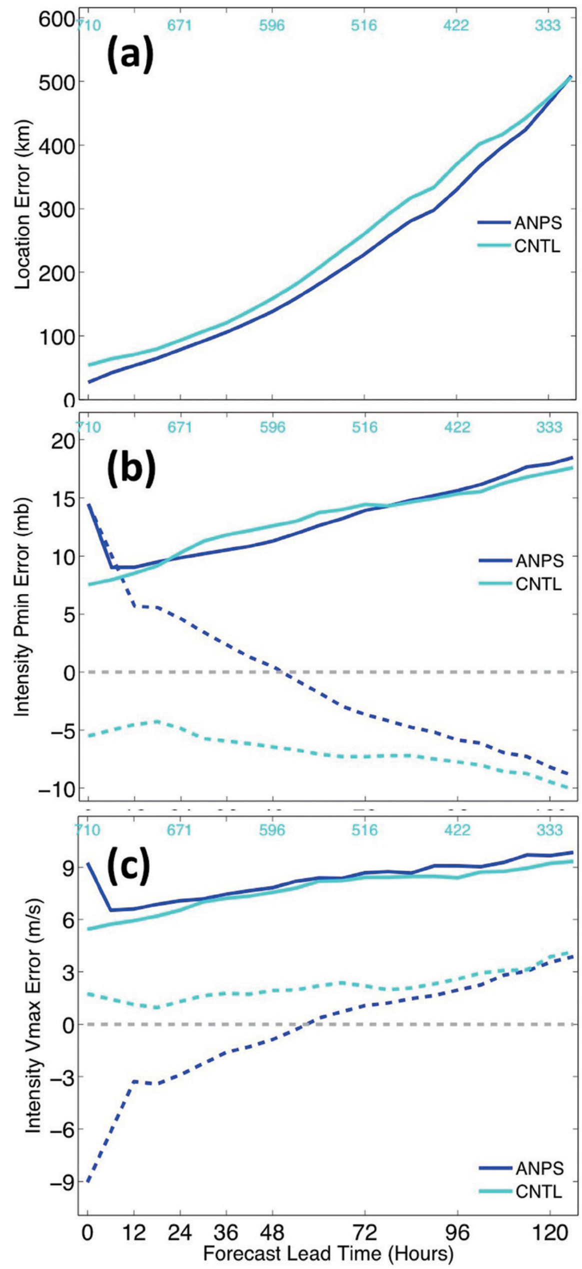

Fig. 3. Mean absolute forecast error (solid lines) and bias (dashed lines) averaged over all 758 cases during 2008–2012 for the WRF deterministic forecasts initialized with operational GFS analysis (ANPS, blue) and the WRF deterministic forecasts initialized with cycling the WRF-EnKF analysis with conventional observation assimilation (CNTL, cyan) for (a) track position error (km), (b) minimum sea level pressure (mb), and (c) 10-m maximum wind speed (m s^{-1}). The numbers of homogeneous samples are listed at the top of each panel.

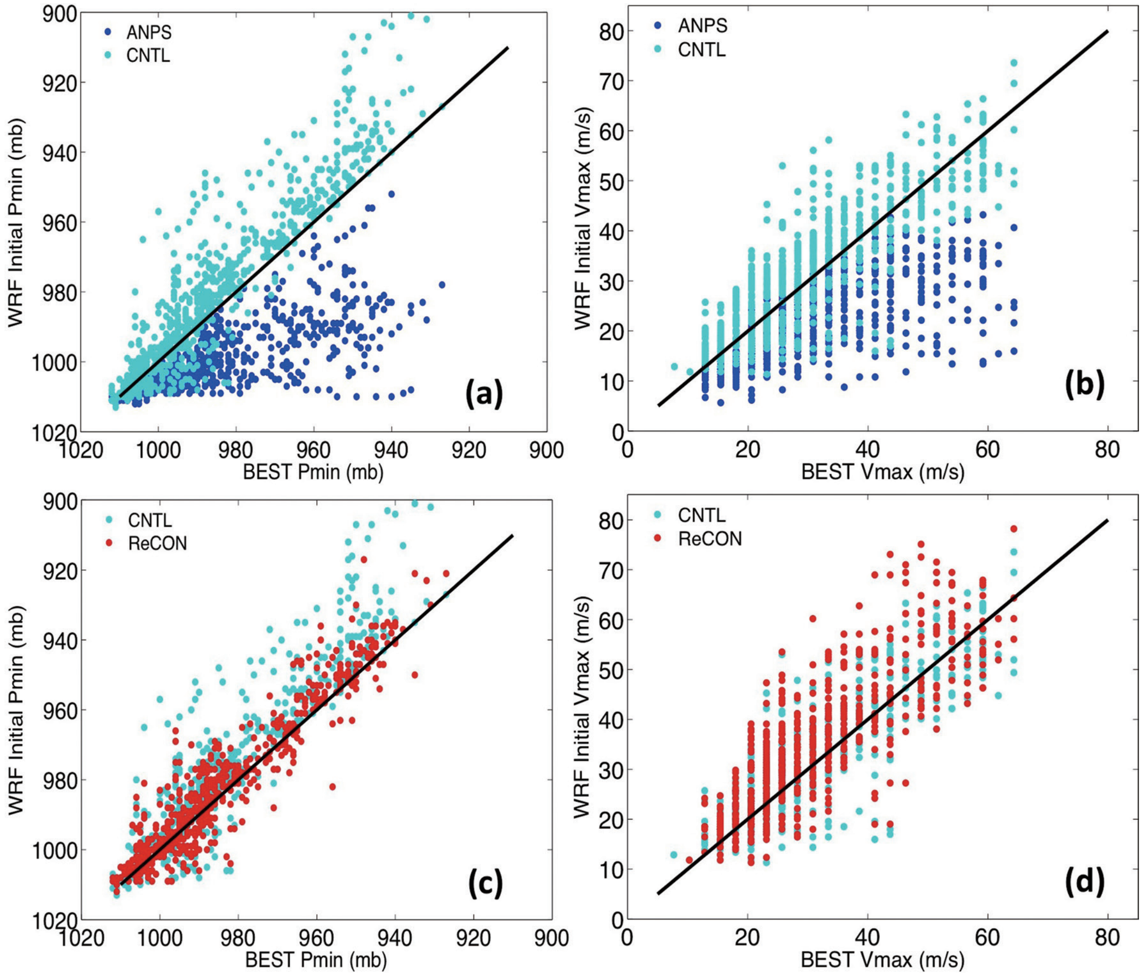

Fig. 4. Initial (a, c) Pmin (mb) and (b, d) Vmax (m s^{-1}) comparison between (a, b) ANPS and CNTL and (c, d) CNTL and ReCON against BEST Pmin and Vmax.

the WRF-EnKF forecasts to determine the TC location, Pmin, Vmax, and structure at every 6 h interval. The averaged absolute forecast error refers to BEST, homogenized with all corresponding experiments over the all cases. This is used to evaluate the data impact.

3. Performance of the baseline cycling WRF-EnKF (CNTL) for selected cases

Before conducting and evaluating the ReCON experiment, it is desirable to examine whether the cycling WRF-EnKF analysis and prediction system in CNTL can provide dynamically reliable TC forecasts with acceptable accuracy through comparing its forecasts with those that are directly initialized with the operational global analysis without regional-model data assimilation as ANPS in Zhang et al. (2014), which is initialized with the GFS analysis and with the same WRF configuration as in this cycling WRF-EnKF system. Zhang et al. (2014) demonstrated that the ANPS performance is comparable to two operational regional-scale dynamical models (HWRF and GFDL), although slightly inferior to the NHC official forecasts (their Fig. 2).

Figure 3 shows a homogenized comparison of the track and intensity errors and biases in the terms of Pmin and Vmax between forecasts of ANPS and CNTL. The CNTL track forecast error is slightly (10–30 km) larger within the 108-h lead time than that of ANPS (Fig. 3a), but the difference is not significant. For the intensity forecasts, the differences in both terms of minimal sea level pressure (Fig. 3b) and maximal surface wind speed (Fig. 3c) are small.

CNTL has smaller errors for all lead times than those of ANPS (Fig. 3c); the improvement in CNTL is likely from a much reduced intensity bias, especially at the initial time. The biases for ANPS at the initialization time are 15 mb and –17 knots for Pmin and Vmax, respectively, while those of CNTL are –5 mb and 4 knots, respectively. Figures 4a and 4b further show all initial Pmins and Vmaxs for ANPS and CNTL by comparing to BEST. This comparison shows a better correlation between CNTL and BEST than that between ANPS and BEST and indicates the cycling positive impacts on storm intensity initialization. The weak biases of ANPS are partly due to the WRF cold-start initialization from the coarse resolution of the GFS analysis, while the WRF warm-start initialization through the cycling EnKF analysis may reduce such bias.

Overall, the above comparison shows that the track and intensity forecast from the baseline control experiment CNTL with the cycling WRF-EnKF is quite reasonable and comparable to the state-of-the-art regional-scale dynamical prediction systems.

4. Performance of assimilating the reconnaissance data with the cycling WRF-EnKF

With the 3-h cycling WRF-EnKF hurricane analysis and prediction system, we conducted all 636 ReCON cases listed in Table 1 for 23 storms during the 2008–2012 Atlantic hurricane seasons. ReCON starts with the priors of CNTL just before the aircraft mission and ends when there is no further aircraft mission available for the same storm. For example, NOAA started the first aircraft mission at 1225 UTC 27 August 2010 and ended the last mission at 0828 UTC 4 September 2010 for Hurricane Earl (2010), during which there were 35 reconnaissance aircraft missions conducted by NOAA and the USAFR combined (mission information is available at http://www.aoml.noaa.gov/hrd/Storm_pages/earl2010/mission.html). In this case, the ReCON experiment for Hurricane Earl (2010) starts at 1200 UTC 27 August and ends at the same time as CNTL at 0000 UTC 4 September 2010 with a 3-h data assimilation cycle. With the EnKF assimilation, we conduct deterministic forecasts every 6 h, all of which are used for verification. Some cycles without any reconnaissance data to be assimilated are also included in the verification statistics since the forecasts can still be affected by assimilation if the aircraft observations during earlier assimilation cycles.

Figure 5 shows the homogenized comparison of the track and intensity errors of CNTL and ReCON

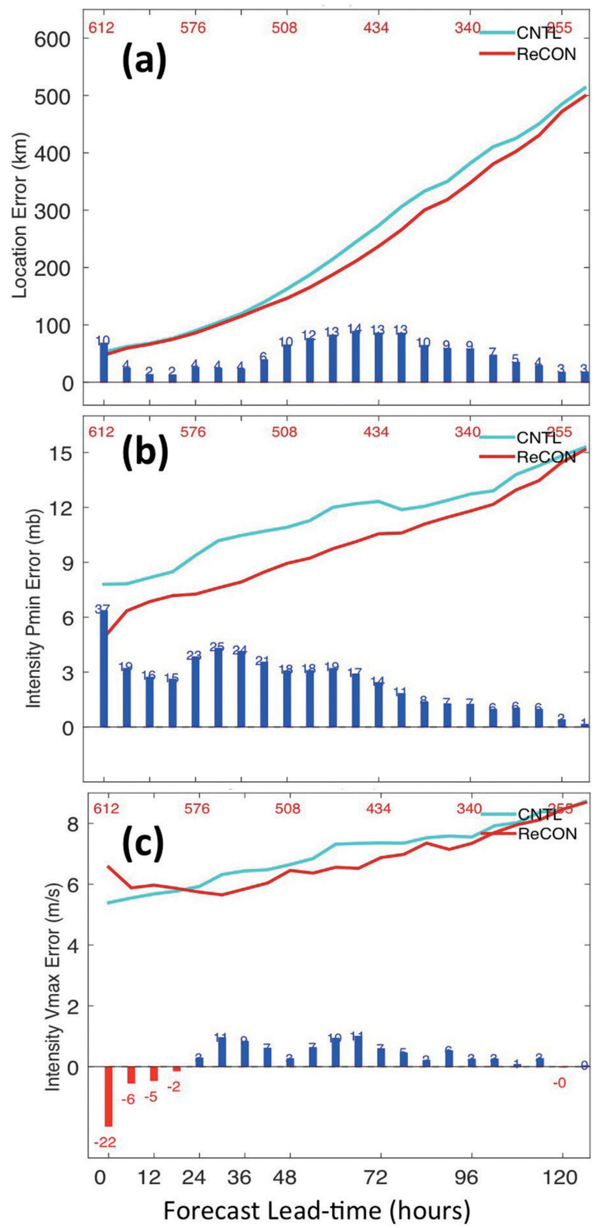

Fig. 5. Mean absolute forecast error in homogeneous verification averaged over all 636 ReCON cases during 2008–2012 for CNTL (cyan) and ReCON (red) for (a) track position error (km), (b) minimum sea level pressure (mb), and (c) 10-m maximum wind speed (m s^{-1}). The blue bar at the bottom of each panel means the improvement of ReCON in percent over CNTL, while the red bar means ReCON is worse than CNTL. The numbers of homogeneous samples are listed at the top of each panel.

Table 2. Real-time reconnaissance cases for 2013 Atlantic storms.

Storm	Cases	Date (YYYYMM: DDHHs)
AL03 Chantal	7	201307: 0912, 1000, 1006, 1012, 1100, 1106, 1200
AL04 Dorian	9	201307: 2400, 2412-2612 every 6h
AL05 Erin	4	201308: 1800-1818
Al06 Fernand	6	201308: 2500-2512, 2600-2612
AL07 Gabrielle	14	201309: 0418-0500, 0518, 0618, 0706, 0718-0806, 1006-1112
AL10 Ingrid	21	201309: 1118-1618
AL11 Jerry	8	201309: 3000-3012, 201310: 0112-0118, 0206, 0218, 0300
AL12 Karen	22	201310: 0100-0606
AL13 Lorenzo	12	201310: 2118-2412
AL95 Invest*	11	201309: 1800-2012
AL98 Invest*	11	201310: 0706-0918
Total	125	Data source: ftp://ftp.nhc.noaa.gov/atcf /archive/2013

*The forecasts for Invest were removed from NHC ATCF archive folder.

verified against BEST. The ReCON experiment with EnKF assimilation of reconnaissance data clearly improves over CNTL for both the track and intensity forecasts at all lead times (except for intensity for the first 18 h). The track errors have from 2 % to 14 % improvements with the reconnaissance data assimilation; specifically, there are more than 10 % improvements for the forecasts within 48–96-h lead times. The improvement of the track forecast may be primarily due to two reasons: one from the improvement of the storm structure that may improve the forecast of the track and the second from the spread of the reconnaissance observation to a large radius of influence that may improve the environmental fields.

The improvement of the intensity forecast in terms of Pmin is the most impressive with the ReCON experiment; the Pmin error is 37 % smaller than CNTL at the initial time and 14 %–25 % smaller within 72-h lead times. Even with slightly larger intensity errors in the terms of Vmax at the initial time likely due to the spin-up of WRF, ReCON has overall 1 %–11 % persistent improvements over CNTL during the lead times of 24–114 h.

5. Performance with reconnaissance data in real-time experiments of 2013

To further evaluate the performance of reconnaissance observation assimilation, the continuously cycling hurricane analysis and prediction system has been selected to take part in 2013 HFIP "Stream-1.5" activities and has been identified as "APSU" by NHC. "Stream 1.5" is a quasi-operational real-time experiment established by HFIP and NHC to evaluate forecast models and/or techniques based on hindcast assessments (http://www.ral.ucar.edu/projects/hfip/includes/HFIP_Stream_1.5_Concept_of_Operations_FY11_20110121.pdf). The verification made by the HFIP TCMT Stream 1.5 Analysis Team based on the ReCON cases listed in Table 1 shows improvements in both track and intensity forecasts with reconnaissance observation assimilation (the verification report is available online at http://www.ral.ucar.edu/projects/hfip/includes/h2013/2013_stream1.5-PSU-update-13Junedata-final.pdf).

During the 2013 Atlantic hurricane season, there were superobservations (SOs) for 15 NOAA airborne TDR missions available including NOAA P-3 and G-IV aircrafts (SOs are available online at ftp://ftp.aoml.noaa.gov/hrd/pub/gamache/FuqingSO). However, due to the United States government lockdown and the issue of TDR data processing, the APSU system did not receive any Doppler radar SO file in real time, and the real-time system did not assimilate any TDR observations. This makes the real-time APSU runs the same as the above ReCON experiment. There were 14 storms and about 640 total cases based on real-time TCVitals in the 2013 Atlantic hurricane season. Because of the computing resource issue, we only delivered 125 cases to NHC on time. Table 2 lists the 125 cases, and all hurricane forecasts

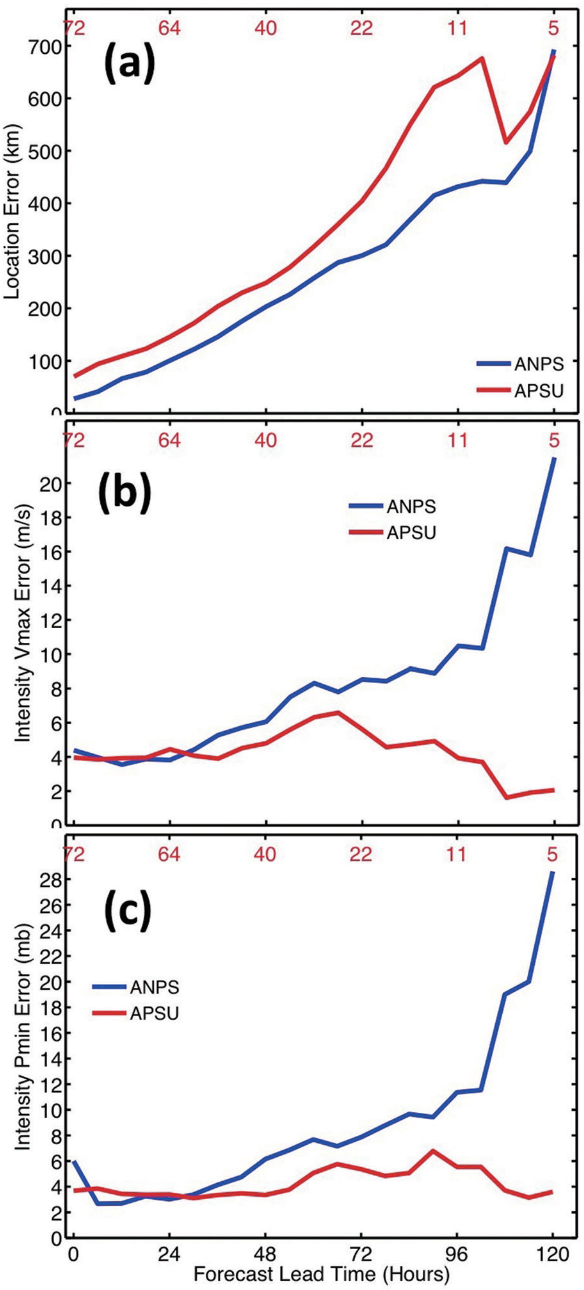

Fig. 6. Mean absolute forecast errors in homogeneous verification averaged for 2013 stream 1.5 APSU (red) and ANPS (blue) for (a) track position error (km), (b) minimum sea level pressure (mb), and (c) 10-m maximum wind speed (m s^{-1}). The numbers of samples are listed at the top of each panel, and all cases are available in the ATCF a-deck files.

of the 125 cases are available on online at the NHC's ftp server: ftp://ftp.nhc.noaa.gov/atcf /archive/2013.

To identify the real-time performance of the cycling hurricane analysis and prediction system with reconnaissance data assimilation, we compare APSU (ReCON) with the hindcasts by the ANPS configurations that are initialized with the operational GFS analysis. Figure 6 shows the homogeneous errors of ANPS and APSU for track and intensity forecasts. The comparison shows that the cycling reconnaissance data assimilation system decreases the track forecast accuracy (Fig. 6a), but the intensity forecasts in terms of both Vmax (Fig. 6b) and Pmin (Fig. 6c) are largely improved. By comparing APSU to the NHC official forecasts (OFCL) and the dynamical forecasts by the two NOAA regional models HWRF and GFDL (Fig. 7), it is found that the intensity forecast error of APSU is significant smaller than those of OFCL/HWRF/GFDL despite a slight degradation in the track forecast accuracy.

6. Concluding remarks

This article first presents an overview of the recent advances in analysis and prediction of tropical cyclones through assimilation of reconnaissance aircraft observations. We further present a cycling WRF-EnKF analysis system to evaluate the impact of reconnaissance data assimilation on hurricane intensity forecasting. The control experiment CNTL is set to assimilate all conventional observations and satellite-derived winds except the reconnaissance data. The forecast result of the control experiment has the same forecast accuracy as the baseline forecast ANPS, which is the same configured WRF model initialized with operational GFS analysis and has the smallest track and intensity forecast errors compared to the NHC regional dynamical hurricane models HWRF and GFDL over 2920 cases during the 2008–2012 Atlantic hurricane seasons (Zhang et al. 2014).

The reconnaissance data impact experiment ReCON is initialized with the priors of CNTL and assimilates all conventional observations, satellite-derived winds, and the reconnaissance data including flight-level observations and dropsondes every 3 h. The verification shows positive impacts on hurricane track and intensity forecasts by assimilating reconnaissance data; the reconnaissance data assimilation reduces position forecast errors by 2 %–14 % and minimal sea level pressure forecast errors by 1 %–37 % for each lead time during 0–126 h and reduces maximal 10-m wind speed forecast errors by 1 %–11 % during the 24–114 h lead times over all 636 cases

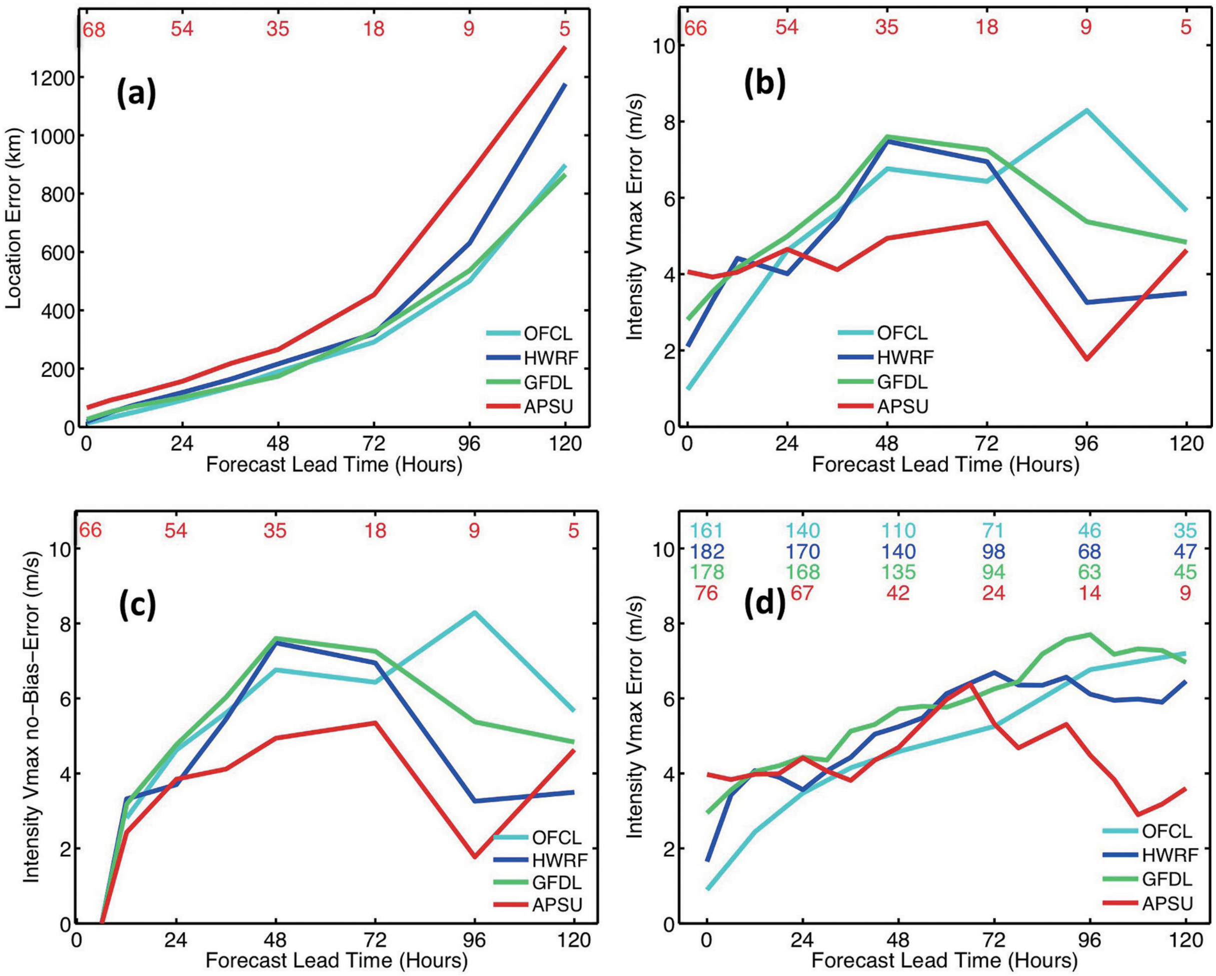

Fig. 7. Mean absolute forecast errors averaged for 2013 stream 1.5 APSU (red), operational OFCL (cyan), HWRF (blue), and GFDL (green). Homogeneous verification for (a) track forecast errors (km), (b) intensity forecast errors (m s^{-1}), (c) intensity forecast errors (m s^{-1}) with late model interpolation, and (d) intensity forecast errors (m s^{-1}) averaged for all cases for each forecast. The numbers of samples are listed at the top of each panel, and all cases are available in the ATCF a-deck files.

during 2008–2012 compared to the control experiment.

The real-time implementation of the continual cycling EnKF system with reconnaissance data assimilation makes remarkable improvements in hurricane intensity forecasting by comparing the no-data-assimilation forecasts and NHC operational official forecasts and two main regional hurricane dynamical model forecasts.

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