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ABSTRACT

Ensemble-based data assimilation (EDA) has been used for tropical cyclone (TC) analysis and prediction with some success. However, the TC position spread determines the structure of the TC-related background error covariance and affects the performance of EDA. With an idealized experiment and a real TC case study, it is demonstrated that observations in the core region cannot be optimally assimilated when the TC position spread is large. To minimize the negative impact from large position uncertainty, a TC-centered EDA approach is implemented in the Weather Research and Forecasting (WRF) Model-local ensemble transform Kalman filter (WRF-LETKF) assimilation system. The impact of TC-centered EDA on TC analysis and prediction of Typhoon Fanapi (2010) is evaluated. Using WRF Model nested grids with 4-km grid spacing in the innermost domain, the focus is on EDA using dropsonde data from the Impact of Typhoons on the Ocean in the Pacific field campaign. The results show that the TC structure in the background mean state is improved and that unrealistically large ensemble spread can be alleviated. The characteristic horizontal scale in the background error covariance is smaller and narrower compared to those derived from the conventional EDA approach. Storm-scale corrections are improved using dropsonde data, which is more favorable for TC development. The analysis using the TC-centered EDA is in better agreement with independent observations. The improved analysis ameliorates model shock and improves the track forecast during the first 12 h and landfall at 72 h. The impact on intensity prediction is mixed with a better minimum sea level pressure and overestimated peak winds.

1. Introduction

Tropical cyclones (TCs) can bring catastrophic disasters and lead to great losses in terms of human life and economic interests, which is a major concern and challenge for regional numerical weather prediction (NWP). Although TC track prediction has improved steadily owing to advancements in numerical models and data assimilation of increased satellite observations over the last few decades, the progress in TC intensity forecasting has been modest (Rappaport et al. 2009). There are a number of factors that may contribute to the limited forecasting skill in TC intensity. Recent studies have shown that intrinsic predictability is more of a limiting factor for TC intensity than for TC track (Judt et al. 2016; Judt and Chen 2016; Kieu and Moon 2016). The lack of coupling to the ocean is a major shortcoming in many current prediction models (Chen et al. 2007, 2013). Another limiting factor in the current TC prediction system may be due to the relatively poor representation of the TC structure and intensity in the initial conditions for TC forecasting (Kurihara et al. 1993). To tackle these difficult problems, efforts have been made to improve the model physics and mimic the real TC structure using vortex initialization techniques.

Generally speaking, TC vortex initialization methods can be categorized into four groups. They are vortex bogusing (Ueno 1989; Leslie and Holland 1995; Pu and Braun 2001), dynamical initialization (Kurihara et al. 1993, 1995, 1998; Nguyen and Chen 2011), vortex relocation...
(Liu et al. 2000; Hsiao et al. 2010), and data assimilation (DA) (Zou and Xiao 2000; Chen and Snyder 2007; Torn and Hakim 2009; Zhang et al. 2011). These methods are used alone or in combination to generate a TC vortex in the model initial conditions and have led to some degree of success. Among these methods, DA is the only method that uses observations obtained in TCs and/or TC environments with the proper description about the accuracy of these observations.

Previous studies have used either a synthetically generated TC vortex or real observations to represent TC structures that can be assimilated into a DA system. The former is also referred to as bogus data assimilation (BDA) and is usually adopted within a variational DA framework. BDA implemented in three- or four-dimensional variational analysis systems has yielded positive results in representing idealized (“bogus”) TC structures and improving TC predictions (Zou and Xiao 2000; Pu and Braun 2001; Chou and Wu 2008; Davidson et al. 2014). However, in the early work on variational methods, the background error covariance used is usually static and not able to represent the TC-related uncertainty; hence, the observations cannot be used effectively to correct errors related to TC circulation. In contrast, the ensemble Kalman filter (EnKF; Evensen 1994), which uses flow-dependent background error statistics to consider the dynamical uncertainty in TC circulation naturally, has the advantage of assimilating the observations more effectively (Yang et al. 2013) and is expected to fit better with TC DA and prediction (Hamill et al. 2011a,b). Building on the advantages of EnKF and variational methods, significant work with the hybrid variational–EnKF system has also shown positive results for TC assimilation and prediction (Poterjoy and Zhang 2014; Lu et al. 2017).

Within the EnKF framework, strategies have been developed to assimilate observations to improve TC structures in the analysis. Chen and Snyder (2007) were the first to propose an idea for assimilating the TC advisory information issued by operational centers [e.g., center location, minimum sea level pressure (MSLP), and peak wind] in addition to other observations to improve the vortex initialization. Using a simple two-dimensional barotropic model, they showed that the track forecast initialized from such TC-targeted EnKF analysis is improved with a reduced spurious transient evolution of the initial vortex. Wu et al. (2010) further advanced the assimilation of TC advisory data by frequently assimilating parameters related to the TC track and structure, including the center position, velocity of TC motion, and axisymmetric surface wind. They showed that after the initialization period, a realistic initial TC vortex can be produced. With their EnKF system, even when only surface wind data are assimilated, a reasonable vertical TC structure can be successfully established in some cases. More specifically, such data can help generate the classic in–up–out secondary circulation of TCs. Moreover, regional EnKFs implemented in cloud-resolving models can assimilate data at high spatial and temporal resolutions, which also have a major impact on TC structure and intensity forecasts. Studies suggest that the key to improving the intensity prediction relies on the ability to represent both the TC inner-core structure (Zhang et al. 2009; Weng and Zhang 2012) and environmental conditions (Wu et al. 2014).

One of the advantages of the ensemble-based method on TC assimilation is that it takes into account the collective flow-dependent uncertainties associated with TC center location and intensity, as well as the environment, which determine the TC evolution. However, the TC position uncertainty in EnKF remains a major challenge. It can dominate the performance and affect the accuracy of the analysis. For the mean state, averaging the TC in all ensemble members with different center locations yields an overly smoothed and weak TC, with an overestimated size and ill-defined inner-core structure. If the position spread is not well constrained and becomes too large, unrealistic features, such as double vortices, can occur near the core region (Chen and Snyder 2007). For the ensemble-estimated background error statistics, the position uncertainty dominates the background error statistics and can mask the uncertainties associated with the TC structure and intensity (Torn and Hakim 2009; Poterjoy and Zhang 2011). Excessive variance in the TC position of the ensemble results in asymmetric corrections that can distort the vortex structure. Even small changes in the modeled TC position may cause a large unrealistic covariance near the TC eyewall where large gradients are located. Poterjoy et al. (2014) also reported that the vortex-scale analysis increment is sensitive to the ensemble variance at the inner core. Therefore, large uncertainties in storm position can significantly degrade the performance of the EnKF analysis in TC initialization.

To address this issue, methods have been proposed to tackle the TC location uncertainty in EnKF. Chen and Snyder (2007) suggest that assimilating the TC position prior to the assimilation of other observations can reduce the TC position uncertainty and produce a more accurate TC analysis. Some studies suggest that assimilating MSLP from TC advisory data as a standard SLP observation helps to constrain the TC position and improve the intensity (Hamill et al. 2011a; Kleist 2011). However, if the TC center in the background state is too far away from the MSLP observations, an issue of an artificially created double eye will be problematic
(Kawabata et al. 2012). To avoid such an issue, Kunii (2015) adopted the concept from Chen and Snyder (2007) to use the MSLP of the model state as the background field, instead of the simulated SLP value at the observed TC location when assimilating the MSLP observations. A recent study by Navarro and Hakim (2014, hereafter NH14) proposed a storm-relative ensemble assimilation method for EnKF to relocate the TC ensemble to the observed TC position before performing the storm-scale assimilation. They showed that by using the storm-relative approach, the vortex has a finer inner core with a more realistic asymmetric structure compared to the truth state, whereas the conventional EnKF analysis can produce errors greater than an order of magnitude in some cases. Although NH14 demonstrated the potential of the storm-centered approach for TC assimilation in an idealized observing system simulation experiment (OSSE) using a dynamically simple shallow-water model and uniformly distributed observations, the impact on TC prediction with full-physics NWP models and realistic observations in TCs has not yet been investigated.

In this study, we first demonstrate the importance of representing the TC position uncertainty in the TC ensemble-based DA (EDA) within an idealized framework and examine the impact of constraining the position uncertainty in a regional EnKF system with in situ field observations of a real typhoon case. The regional EnKF system consists of the Weather and Research and Forecasting (WRF) Model and a local ensemble transform Kalman filter (LETKF). In addition to the conventional WRF-LETKF system, the TC-centered (TCC) DA approach following NH14 is implemented. The capability of the TCC WRF-LETKF system is investigated based on a case study of Typhoon Fanapi (2010), which was a well-observed TC during the Impact of Typhoons on the Ocean in the Pacific (ITOP) field campaign (D’Asaro et al. 2014).

This paper is organized as follows. In section 2, the impact of position uncertainty on TC assimilation is illustrated under ideal scenarios. Section 3 introduces the framework of the TC-centered ensemble data assimilation method. Typhoon Fanapi (2010) is introduced in section 4. The model and experimental setup are given in section 5. The results of the experiments are presented in section 6. Finally, section 7 provides a summary and some discussion.

2. Impact of TC position uncertainty in an idealized framework

To illustrate the importance of TC position uncertainty within the ensemble-based data assimilation framework, we examine the relationship among TC position error, spread, and corrections to TC structure from the single-observation assimilation experiments in idealized scenarios. Five experiments with different types of uncertainties related to TC position and intensity are presented here (Table 1). The uncertainty, represented by ensemble spread, is defined as the dispersedness of the ensemble and is quantified by the standard deviation. In each experiment, 1000 symmetric vortices with their position and/or intensity perturbed are used as the background TC ensemble, and we examine the impact of EDA on TC structure. The large ensemble size is used to avoid the issue of sampling error and to maintain the symmetry in the mean TC structure before assimilation. The symmetric vortex is generated based on the sea level pressure and tangential wind profile in Holland (1980), with parameters of MSLP, pressure of TC environment $P_{env}$, radius of maximum wind (RMW), and shape. We note that the shape parameter is set to 1.0 for all experiments in order to focus on the TC intensity uncertainty.

The experiments are as follows: 1) the TC ensemble has a position spread of 5 km but no differences in intensity (P5); 2) the same as in the first experiment but with a larger position spread of 30 km (P30); 3) the TC ensemble has differences in intensity, but no position spread (I2); 4) the same as in the first experiment but with intensity spread (P5I2); and 5) the same as in the second experiment but with intensity spread (P30I2).

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Position uncertainty (km)</th>
<th>Intensity uncertainty (MSLP; hPa)</th>
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<tr>
<td>P5</td>
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<td>P5I2</td>
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<td>P30I2</td>
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For experiments P5 and P30, the same TC vortex is obtained using an MSLP of 980 hPa, $P_{env}$ of 1010 hPa, and RMW of 50 km, but arranged at different locations to have TC position spreads of 5 or 30 km, respectively. Note that the same vortex is used in the TC ensemble of P5 and P30; thus, the TC uncertainty is contributed by the position uncertainty only. To have the intensity spread in I2, P5I2, and P30I2, we further perturb the MSLP with a standard deviation of 2 hPa (leading to a $1 \text{ m s}^{-1}$ standard deviation in the maximum of the tangential wind). We should note that these parameters, including the TC intensity and spread, are chosen based on the real case of Typhoon Fanapi in 2010 (section 4). Finally, the vortex is arranged in Cartesian coordinates with a grid spacing of 5 km. With these TC ensembles, the EnKF assimilation is conducted to assimilate an MSLP observation (976 hPa; observation error is set to...
1 hPa) under two scenarios: the MSLP observation is 1) located at the center of the mean TC or 2) located 40 km away from the mean TC center. These setups and scenarios are used to mimic the model ensemble states with and without TC relocation and with different degrees of dispersiveness for the position spread. In the following, we focus on how the analysis increment may change the TC intensity and structure. However, we should emphasize that this MSLP could correspond to TC vortices with different characteristics and thus the true TC structure is not specified. The unperturbed TC in the background ensemble (with MSLP of 980 hPa, \(P_{env}\) of 1010 hPa, RMW of 50 km, and shape parameter of 1.0) is used as a reference state to distinguish the structure of the analysis increment.

Figure 1 shows the wind speed of the ensemble mean TC (Figs. 1a–e), analysis increment (Figs. 1f–j), and the azimuthal averaged wind (Figs. 1k–o) under the first scenario. The MSLP observations (gray exes) and the centers of the mean TC are collocated. By comparing the first two columns in Fig. 1, it is clear that the different degrees of position uncertainty can result in different analysis corrections. With a large position uncertainty, the background mean TC structure is overly smoothed out due to the position displacements among the ensemble, resulting in a larger eye and RMW (Fig. 1l, blue line). Also, the horizontal scale and magnitude of the zonal wind ensemble spread increase with the uncertainty in the TC position (Figs. 1f,g, green contours), leading to strong, broader-scale analysis corrections in both the wind and SLP fields. Although the intensity, especially near the RMW, can be greatly increased given a large position uncertainty and innovation (e.g., Fig. 1l), the correction for the inner core leads to a larger RMW and change in the TC structure compared with the reference TC. When the intensity uncertainty is included, the results show that the ensemble spread and analysis correction are dominated by the large position uncertainty. More specifically, the correction of the TC structure is determined by position uncertainty instead of the intensity uncertainty itself. In contrast, the TC ensemble with intensity uncertainty only or an additional small position uncertainty can have the storm-scale correction to enhance the TC circulation, as shown in
Figs. 1m and 1n. The correction is now associated with the intensity uncertainty, rather than being overwhelmed by a large position spread.

In the second scenario (Fig. 2), there is position error in the mean state (i.e., a situation without TC relocation), and the MSLP observation is 40 km away from the center of the background mean TC. The results from experiments with position uncertainty indicate that the TC vortex can be shifted toward the observed TC location after assimilating the MSLP observation. Comparing P5 and P30, when the TC position spread is large enough, the TC vortex can shift very close to the observation location, as shown in Figs. 2b and 2e. However, although the TC position has been corrected, an asymmetry component is introduced at the northeastern sector of the TC, along the line between the observed and mean TC positions. The larger the position spread, the larger the asymmetric component. As pointed out earlier in Fig. 1, the strong correction in P30 and P30I2 brought about by the large ensemble spread corrects the intensity, and the eye and RMW become larger than the reference TC structure. Also, the large position uncertainty dominates the analysis increment, and the difference between P30 and P30I2 in intensity correction is less significant (Figs. 2l,o). With no position uncertainty (I2), the TC position does not move toward the observations, and the intensity becomes much enhanced compared to the I2 experiment in scenario 1. This implies that without relocation, the position error in the mean state can result in overcorrected intensity since the MSLP is mistakenly regarded as an SLP observation near the eyewall, and the corrections enhance the whole TC circulation. When both intensity uncertainty and small position uncertainty (P5I2) are present, the correction can also successfully enhance the TC for both the inner structure (100 km) and the outer circulation (>100 km) without changing the TC structure too much, despite the fact that the correction for the position error is limited. As expected, the TC intensity development based on the TC structure of the P5I2 and P30I2 analyses can be very different.

The negative impact of TC position uncertainty on ensemble TC assimilation results through the averaging of the mean state and structure of the background error covariance. We should note that in other DA systems, such as deterministic EnKF or hybrid approaches, the issue of averaging is not a concern. However, the ensemble-based background error covariance can still carry the information about position uncertainty, and, thus, large position uncertainty can still dominate the background error covariance and still induce
unrealistically large corrections to the TC structure, especially in the inner-core region.

As a conclusion from the experiments of the idealized scenarios, the position uncertainty should be first taken care of in the ensemble-based TC assimilation, in order to use the observations in the inner-core regions of the TC to correct the intensity. Otherwise, the structure of the intensity correction will be overwhelmed by the position spread. For such a purpose, a vortex relocation scheme can be applied to correct the position error and to eliminate the position uncertainty in the ensemble. We should note that if the relocation is only performed on the mean state, the TC position uncertainty can still dominate the ensemble-based error statistics and degrade the analysis performance.

3. TC-centered ensemble data assimilation framework

In the second part of this study, we focus on the investigation of the impact of TC position uncertainty on the analysis and forecasting of a real observed typhoon using a regional EnKF assimilation system implemented in a full-physics numerical model. As demonstrated in an idealized experiment, TC position uncertainty and position error in the mean state during the ensemble-based TC assimilation can bring negative impacts to the TC structure when the position spread becomes large. To reduce such effects, the TC-centered approach used by NH14 is adapted in this study. We made a number of adjustments for implementation in the nested domains of the WRF Model with the EnKF assimilation system. Our experiment is carried out in the following three steps (similar to the process described in NH14). 1) A conventional data assimilation experiment is conducted to provide an analysis of the TC environment over the WRF’s outer domain. 2) Because the TC center of each ensemble member is located at the center of the vortex-following inner domain, we relocate the center of the inner domain of all ensemble members to the observed TC location. The TC-centered data assimilation process is then performed to generate an analysis in the TC area within the inner domain. 3) The results from steps 1 and 2 are merged together with the same method used in NH14. The merging process is performed by linearly combining two analyses over a finite area, defined by a concentric ring around the TC. The weight on the conventional analysis is given by

$$w = 1 - \left(\frac{\cos \frac{\pi r}{2}}{2}\right)^2.$$  \hspace{1cm} (1)

In Eq. (1), \(r = (r - R_{in})(R_{out} - R_{in})\), where \(r\) is the radial distance from the TC center, and \(R_{in}\) and \(R_{out}\) are, respectively, the inner and outer radii of the concentric ring where we merge the two analyses. The outer radius \(R_{out}\) is 280 km, close to the size from the typhoon advisory dataset, and the inner radius \(R_{in}\) is three-quarters of the outer radius \(R_{out}\), which is 210 km in this case.

4. Typhoon Fanapi of 2010

Typhoon Fanapi developed from a tropical depression east of the Philippines on 14 September 2010. After its formation, Fanapi moved northwestward and gradually intensified into a tropical storm (TS) on 15 September. During its early stages, Fanapi moved slowly and turned northeastward on 16 September. Starting at 0000 UTC 17 September, Fanapi curved toward the northwest again and then moved westward after 1200 UTC 17 September. While moving westward, Fanapi reached its peak intensity with an MSLP of 944 hPa and maximum wind speed (MWS) of 54 m s\(^{-1}\) at 0600 UTC 18 September. After making landfall in Hualien County in Taiwan at 0000 UTC 19 September, Fanapi weakened drastically as a result of destruction by topographic effects, and the storm dissipated a few hours later after its second landfall over China on 20 September.

Typhoon Fanapi is selected in this study because it is the best observed TC during the ITOP\(^1\) (D’Asaro et al. 2014) field campaign in 2010. During the life cycle of Fanapi, numerous dropsonde, airborne, and satellite observations were made in the inner-core regions, and we used many for our data assimilation experiments and verification.

5. Model, assimilation, and experimental setup

a. Model and experimental setup

The TC-centered ensemble data assimilation method is implemented within the WRF-LETKF framework. WRF-LETKF (Yang et al. 2013, 2014) is a regional data assimilation and prediction system that consists of the Advanced Research version of the WRF Model,
version 3.6.1 (Skamarock et al. 2008), with a vortex-following nested grid capability (Tenerelli and Chen 2001) and LETKF (Hunt et al. 2007) data assimilation systems. The performance of this new TC-centered EnKF system is evaluated based on a case study of Typhoon Fanapi (2010), and the impact is investigated by comparing a conventional DA experiment, which uses the conventional WRF-LETKF system, with the experiment using the new TC-centered WRF-LETKF framework. The conventional DA experiment is hereafter referred to as CTL and the new TC-centered experiment as TCC.

In CTL, the WRF Model is executed with two-way nested domains. The horizontal grid spacings of the outer and inner domains are 12 and 4 km, with dimensions of $600 \times 445$ and $403 \times 403$ grid points, respectively. There are 36 vertical layers in both domains with a model top up to 50 hPa. The physical parameterizations include the WSM 5-class microphysics scheme, the RRTM scheme for longwave and shortwave radiation, the MM5 surface-layer scheme, the YSU PBL scheme, and the Kain–Fritsch scheme for cumulus parameterization (outer domain only). The configuration for the TCC experiment is mostly the same as that of CTL, except the inner domain is vortex following with $151 \times 151$ grid points in order to implement the TC-centered DA. For a fair comparison, the merging process in TCC is also performed in CTL so that the TC vortex analyses are from the inner domain and the analyses of the TC environment are from the outer domain.

Both experiments are cold started at 1200 UTC 12 September 2010, in which 36 ensemble members are initialized by adding perturbations, randomly drawn from the three-dimensional variational data assimilation (3DVAR) background error covariance (Torn et al. 2006), to the NCEP GDAS $1^\circ \times 1^\circ$ analysis dataset. (Available online at https://doi.org/10.5065/D6M043C6.) After a 12-h ensemble forecast to spin up the model, the first LETKF analysis is conducted at 0000 UTC 13 September followed by 6-h forecast–analysis cycles until 0000 UTC 16 September. Afterward, a 3-day forecast is initialized from the analysis ensemble mean at 0000 UTC 16 September. A covariance localization scale of 150 km is adopted for the outer-domain assimilation and 50 km for the inner-domain assimilation. The TC-centered DA is conducted at 1800 UTC 14 September, after the vortex in the CTL experiment has been spun up by assimilating the synthetic vortex winds that will be described in the next subsection. In other words, before 1800 UTC 14 September, both experiments are identical (Fig. 3).

b. Assimilated data

Sources of the observations assimilated here include surface stations, rawinsondes, aircraft reports, mid-to-upper-level atmosphere motion vectors (AMVs), the MSLP of the TC from the Joint Typhoon Warning Center (JTWC), and dropsondes from the ITOP field campaign in 2010 (D’Asaro et al. 2014). For quality control, observations are rejected when the innovations (i.e., the difference between the background and observation) are greater than 5 times the observation errors. In addition, the AMV data are averaged within a cylinder of 100-km radius and a layer of 25-hPa depth, similar to a strategy of superobservation adopted by Wu et al. (2014).

In ensemble-based TC assimilation systems, the assimilation of the TC’s position is often used to constrain that position (Chen and Snyder 2007; Torn and Hakim 2009; Wu et al. 2010). Torn and Hakim (2009) have suggested that assimilating the TC position frequently may partially reduce the large TC position spread. However, Wu et al. (2010) showed that although assimilation of the TC position can reduce the TC position error, it has limited impact on the near-surface wind structure. This may indicate that some inconsistency between the mass and dynamic fields can be introduced by assimilating TC position information. Within an idealized framework, we found that assimilating the TC position can reduce the TC position error, but at the same time, it also generated an asymmetric structure in the wind fields similar to that found during the assimilation of MSLP observations (Fig. 2). The larger the position spread, the larger the correction to the TC position and also the larger the asymmetries in the wind field. These results demonstrate the potential issues from assimilating the TC position observations during high-resolution TC assimilation. Based on these considerations, we did not assimilate the TC position in our CTL experiment. We note that alternative strategies for correcting the TC position error are possible. For example, Nehrkorn et al. (2015) use the feature calibration and alignment technique to correct the TC position error in background fields.

During the lifetime of Fanapi, dropsondes from penetrating U.S. Air Force C-130 flights were available almost every day. There were also three flights of the Dropwindsonde Observations for Typhoon Surveillance near the Taiwan Region (DOTSTAR; Wu et al. 2005) Astra jet to measure the environment of Fanapi on 15–17 September. As an example, the locations of the dropsondes at 0000 UTC 15 and 16 September are shown in Fig. 4. The importance of these data in providing corrections for improving the
TC environment and structure through data assimilation will be shown in the next section. We also note that instead of treating dropsondes as sounding profiles with a location, each dropsonde data point at each level has its own location to take into account the location drifting as a result of the strong wind speeds in order to represent the inner-core structure correctly.

During the early developing stage of Fanapi, the MSLP of Fanapi is 1004 hPa at 1200 UTC 14 September from JTWC and a small observation increment is obtained, which led to ineffectiveness in establishing a reasonable vortex structure. To spin up the TC structure, additional synthetic winds according to an axisymmetric vortex consistent with the JTWC best-track (i.e., MSLP and MWS) data are assimilated at 0000, 0600, and 1200 UTC 14 September. The generation of the synthetic TC data is adopted from a procedure of bogus data assimilation used in the Coupled Ocean–Atmosphere Mesoscale Prediction System-Tropical Cyclone (COAMPS-TC) for the purposes of TC prediction (Liou and Sashegyi 2012). Note that this type of synthetic TC data cannot fully represent the asymmetric structure in TCs.

6. Results from the real case

a. Analysis

During the early stage of the assimilation, the assimilation of observations, including the bogus vortex assimilation, helps to form the circulation of Fanapi. As shown in Fig. 5, the TC position and intensity (i.e., MSLP and maximum 10-m wind speed) in the analysis mean state approached the observed values at 1800 UTC 14 September. However, in the CTL analysis mean, the TC position and intensity have large fluctuations with poor performance at 1200 and 1800 UTC 15 September. At these times, a poor TC structure in the background mean is obtained as a result of the large position spread. In comparison, TC parameters are well fit with the observed values in the TCC analysis mean. Although at 0000 UTC 16 September, the TC position errors in both the CTL and TCC analysis means are comparable (8.7 km for CTL and 10.5 km for TCC), their MSLP values are very different, indicating that the TC inner-core structures derived from the TC-centered and conventional assimilations are different. As will be discussed in further detail later, the large improvement at 0000 UTC 16 September in the CTL analysis is
attributed to the assimilation of the ITOP dropsondes. We note that the presence of the position error in TCC is because the TC center here is defined by MSLP, whereas in our model setup the center of the vortex-following inner domain is determined by the geopotential height at 850 hPa. When the TC is vertically tilted and the tilting extent could be different for each member, these centers will not be the same.

As pointed out in previous studies and in section 2, the TC position uncertainty in the ensemble dominates the ensemble-based background error covariance and may hinder the performance of the ensemble-based DA. To illustrate the impact of the position uncertainty on ensemble-based DA, we examined the background ensemble mean and the spread from both experiments. Figures 6a and 6c show the mean and spread of the east-west component of the wind from both experiments at 1800 UTC 14 September, where the TC-centered approach is first applied. At this time, the difference between the CTL and TCC experiments is small, because the position spread is still small (i.e., 14 km in CTL and 6 km in TCC). As indicated by the black dots in the top panels in Fig. 6, the TC position spread in CTL increased steadily with time, from 14 km at 1800 UTC 14 September (Fig. 6a) to 24 km at 0000 UTC 15 September (Fig. 6b). The difference in TC structure between the two experiments becomes more noticeable as the position spread increases. At 0000 UTC 15 September, the TC in the background mean of CTL is much weaker and has a larger spread around the TC center than those shown for TCC (cf. Figs. 6b and 6d). With the assimilation of the dropsonde data at 0000 UTC 15 September (Fig. 4a), the position errors (spread) can be reduced in both experiments, from 54.2 to 28 km (from 23.8 to 11.63 km) and from 20.0 to 15.3 km (from 7.6 to 4.6 km), respectively. However, without the dropsonde data at 0600, 1200, and 1800 UTC 15 September, assimilating other observations has a limited impact on constraining the position or shrinking the spread effectively. In particular, the TC structure is too weak in the background mean of CTL, and thus the simulated MSLP is far from the observations, so that the MSLP observations at 1200 UTC 15 September are rejected by the procedure of quality control (QC). We note that if we relax the QC criterion to assimilate MSLP, significant spindown can occur (Tallapragada et al. 2014). In comparison, the MSLP observations can be successfully assimilated into the TCC experiment with a background closer to the observations. This again confirms that the position uncertainties in the ensemble can affect the effectiveness of using observations in the inner-core region of the TC.

As a result of the less constrained position uncertainty, the position spread in the CTL ensemble grows even faster. The position spread in CTL reaches 56 km (Figs. 7a,b) at 0000 UTC 16 September. Except for the large position spread, there is also a significant westward bias in the ensemble TC position. The large uncertainty and bias of the TC position reflect the fact that, during early analysis cycles, the conventional assimilation has not yet well depicted the conditions of the TC environment (e.g., variations in the subtropical high). The spinup period of assimilation can be longer with limited observations over the open ocean and initial ensemble perturbations that are less optimal to represent flow-dependent errors (Yang et al. 2013). As noted in section 2 and in previous studies (Chen and Snyder 2007; Poterjoy and Zhang 2011; Navarro and
Hakim (2014), the large TC position bias and spread lead to a weak mean TC structure and an unrealistically large ensemble spread around the TC center (the same as the P30I2 experiment in scenario 2). The background ensemble of CTL at 0000 UTC 16 September provides evidence for such an issue. As shown in Figs. 7a and 7b, the TC in the background mean state has a very weak and broad structure due to the averaging. The MWS is only 16 m s$^{-1}$ and the MSLP is 998 hPa, compared to the 28 m s$^{-1}$ and 982 hPa values reported by JTWC. In addition, the ensemble spread is unrealistically large in the TC area, such that the spread of the east–west component of the wind at the lowest model level can reach 17 m s$^{-1}$. In contrast, within the TC-centered DA framework, the TCC background mean state (Figs. 7c,d) shows a more compact and intense TC structure with much stronger MWS (31 m s$^{-1}$), lower MSLP (981 hPa), and smaller size. Moreover, the spread of the east–west wind is now reduced to about 8 m s$^{-1}$ in maximum and is confined in the eyewall of the TC. We should note that within the TCC method framework, although all the TCs in the ensemble are relocated to the observed TC center at the corresponding analysis time.

**Fig. 6.** Background ensemble mean (color) and spread (contours) of the east–west component of the wind at the lowest model level for the (top) CTL and (bottom) TCC experiments at (a),(c) 1800 UTC 14 Sep and (b),(d) 0000 UTC 15 Sep. The black dots indicate the center locations of TCs for each member, where the red ex is the center of the ensemble mean. The black dashed line is the track of Fanapi from JTWC with the black circle representing the TC center at the corresponding analysis time.
location, there is still a small TC position spread of about 6–8 km. Such a position spread comes from the uncertainty in the TC structure and the methodology used to define the TC center. Most importantly, this allows us to represent the uncertainty in the TC intensity and structure, without being overwhelmed by position uncertainty.

Having a large position spread in the background ensemble not only leads to a large innovation, it also greatly influences the structure of the background error covariance and analysis correction. Figure 8 shows the point error covariance between the sea level pressure at the TC center and the domain-wise sea level pressure, as well as the east–west component of the wind. Within the range of 50 km away from the center, the features of the point covariance of CTL and TCC are similar, indicating that a negative innovation not only decreases the central sea level pressure, but also enhances the cyclonic circulation of the TC. However, the CTL background error covariance has a larger amplitude and a much wider horizontal scale than that of the TCC background error covariance. This suggests that the CTL background error covariance will result in a strong and wider correction on the background, while the TCC has the smaller
correction confined in the inner core. For example, at this time, the mean position error in the CTL experiment decreased from 187 to 8.6 km.

Although the position error at 0000 UTC 16 September is comparable in both analyses, the characteristics of the TC structure, especially the inner core, are very different. Figure 9 shows the analysis mean and analysis increment of wind speed at 0000 UTC 16 September, at the time when the dropsonde observations from the ITOP field campaign are available. In the CTL experiment (Fig. 9a), the analysis increment is well collocated with the TC structure in the analysis mean state. Such a result indicates that, even with a very poor background state (i.e., a smooth and mislocated TC structure), the EnKF successfully adjusts the position error and attempts to build a vortex structure with the help of the dropsonde information, and the analysis increment determines the TC structure in the analysis mean state. However, although the TC circulation is significantly enhanced, the structure of the TC is still not well constructed. In comparison, with the TC-centered DA, the TCC background mean state (Figs. 7c,d) at this time has already exhibited a stronger and more symmetric TC structure. The analysis correction (Fig. 9d) allows further strengthening of the inner core and shrinking of the eye. Also, the outer (100 km away from TC center) wind speed along the western side of TC has increased. With the same observations, it is clear that the observational influences can be very different given the CTL and TCC background ensembles. We also observed that the structure of the corrections varies greatly among the CTL analysis ensemble members. For the background ensemble member with a TC center already close to the observed TC location (Fig. 9b), the TC looks similar to that of in the TCC analysis mean (Fig. 9d), which has a stronger wind speed in the southeast sector of the inner core. For the background ensemble member with a TC center away from the
observed location (Fig. 9c), the analysis correction behaves like that shown in Fig. 9a, which is wider and collocated with the analysis TC circulation. In contrast, the main characteristics of the TC in the TCC analysis ensemble are relatively similar. For example, the analysis corrections in the TCC ensemble members (Figs. 9e,f) and mean state (Fig. 9d) all show small-scale features near the eye and a broader impact at the outer region (>100 km).

The results from Figs. 8 and 9 also imply that the conventional assimilation results in strong corrections that may not be consistent with the model dynamics, while the TC-centered assimilation builds a more reliable background structure, and observations play a role in fine-tuning the TC structure. With the unrealistically large ensemble spread shown in Fig. 7, we also note that the strong correction in the CTL analysis can lead to model shock, a dramatic adjustment for the model to
As will be demonstrated in the next subsection, forecasts initialized from the CTL analysis may require a longer model spinup period to adjust to a dynamically balanced state.

The use of the TC-centered framework also brings a great positive impact on the vertical development of the TC. As in Fig. 10a, the TC in the CTL background mean has very weak tangential wind with a large radius of maximum wind (~140 km) and weak radial inflow appearing near the surface. After assimilating the dropsonde observations, both the tangential wind and radial inflow are increased (Fig. 10b). However, since the dropsondes were deployed near 700 hPa, analysis correction is limited to the mid- to low levels, and the TC structure in the CTL analysis is shallow. In comparison, the tangential wind, low-level inflow, and upper-level outflow are much stronger in the TC of the TCC analysis mean (Fig. 10d), accompanied by less tilting and a more compact eyewall structure. This indicates that the observations effectively enhance the secondary circulation of the TC in the TCC experiment, resulting in conditions that favor TC development.

To verify the impact discussed above quantitatively, the TC wind speed from the CTL and TCC simulations analyzed at 0000 UTC 16 September are compared to surface wind observations from the Stepped Frequency
Microwave Radiometer (SFMR) on board the C-130 and the Indian Oceansat-2 Scatterometer (OSCAT) instrument. The C-130 reconnaissance carrying the SFMR flew in from the northeastern quarter of the typhoon and ended southeast of the typhoon, as denoted by the thick black solid line in Fig. 9a. The OSCAT surface winds shown in Figs. 9g and 9h were observed at about 0300 UTC 16 September. From Fig. 9g, the OSCAT without rain correction shows that Fanapi has an asymmetric structure, which is stronger on the east side and even stronger in the southeastern quadrant. This pattern is better represented in the TCC analysis (Fig. 9d) compared to the CTL analysis (Fig. 9a). However, we note that the OSCAT observations in the southeastern quadrant have larger uncertainty due to rain contamination, as shown by the white area in Fig. 9h. Figure 11 compares the model to SFMR and OSCAT surface wind speeds (SWSs) in TC-relative coordinates. The large difference between SFMR and OSCAT within 50 km of the TC center indicates that the OSCAT cannot capture the inner-core structure of Fanapi; on the other hand, the SFMR and OSCAT are more consistent at the outer circulation (>50 km) except that the wind speed from SFMR is higher in the southeastern quadrant. For the model results, as shown in Figs. 11a and 11b, there is a strong correction for the CTL background to enhance the wind speed in the inner core, while a relatively small adjustment is needed for the TCC background to further shrink the eye. The TC in the TCC analysis (Fig. 11d) shows in its intensity a much closer resemblance to SFMR than to that of the CTL analysis, and its wind speed in the outer circulation generally agrees better with OSCAT with smaller spread. Such a difference between the CTL and TCC corrections can be more clearly demonstrated with the azimuthal average. As shown in Fig. 12, the TC in the TCC analysis has a radius of maximum wind and 34-kt (1 kt = 0.51 m s\(^{-1}\)) wind closer to the observed values, while the RMW in

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**Fig. 11.** Surface wind speed in TC-relative coordinates. The blue and red dots show results from CTL for the (a) background and (b) analysis at 0000 UTC 16 Sep. (c), (d) As in (a) and (b), but for TCC. The black lines are the surface wind speeds observed by the SFMR on board the C-130 during 2230–0400 UTC 15–16 Sep. The gray dots are the ocean surface wind retrievals from OSCAT observed at 0300 UTC 16 September. The green exes are the dropsonde-observed surface wind speeds; the dropsondes were deployed from the C-130.
the CTL analysis is unrealistically large, indicating a poor representation of the inner structure. When comparing the surface wind speed along the path of the reconnaissance flight carrying the SFMR (Fig. 13), it is evident that the TCC analysis is very successful in depicting the eyewall structure; the stronger wind speed on the eastern side of the TC (also visible in Figs. 9d–f) supports the fact that the asymmetry is better established. With respect to the SFMR, the root-mean-square difference (RMSD) is reduced from 8.7 m s$^{-1}$ with the CTL background to 5.3 m s$^{-1}$ with the CTL analysis, and from 5.8 to 4.2 m s$^{-1}$ for the TCC background and analysis, respectively. Overall, the wind speed has been improved, except for the wind speed corresponding to the SFMR time after 0300 UTC 16 September, when Fanapi is about to transition from a tropical storm into a category 1 hurricane. However, we found that the observed surface wind speed from OSCAT (Fig. 11) and the dropsondes (green exes in Fig. 13) is generally weaker than the SFMR wind speeds during this period. The difference between these observations indicates the presence of uncertainty in the observations. How to address these observation uncertainties remains a challenging issue for verification and data assimilation.

b. Forecast

In this section, we investigate the impact of the TC-centered assimilation on TC predictions based on the forecasts initialized from the CTL and TCC analyses. Discussion focuses on the forecasts initialized at 0000 UTC 16 September (solid lines in Figs. 14 and 15). We note that forecast initialized at the later time (dashed lines in Figs. 14 and 15) is very consistent with the first 3-day forecast, which reinforces that our conclusions remain the same.

Figure 14a shows the 3-day track prediction initialized from the analysis at 0000 UTC 16 September, when Fanapi is about to transition from a tropical storm into a category 1 hurricane. Overall, the track difference between the CTL and TCC forecasts is small, since the corrections for the TC environment from the conventional and TC-centered DA schemes should be similar. Both analyses lead to good track predictions with errors smaller than 100 km for the 3-day forecast. However, the position errors at the initial time are reduced by different means in both analyses. In the CTL analysis, the position error is mainly reduced by the assimilation of dropsondes, but the position in the TCC analysis is constrained by the use of a TC-centered framework. The major difference is that there is a track discontinuity during the first 12-h CTL forecast. This is possibly due to the inconsistency between the model dynamics and the analysis field. Such a result also suggests that within the conventional WRF-LETKF framework, an improperly described TC structure in the background can introduce an imbalanced correction, which is unfavorable to the model dynamics; therefore, significant adjustment to the dynamical balance occurs as the forecast is initialized. In comparison, there is no such spinup issue, but the TC in the TCC forecast moves slightly faster to the west than in CTL after the 1-day forecast. Hence, the forecast track error in TCC is about 10 km larger than in CTL, but after 60-h forecast time, the TC makes landfall at a location closer to the observations (Fig. 14b) with a position error in the landfall location of 44 km compared to 93 km with the CTL forecast. Given the similar environmental conditions in CTL and TCC, the reason that the TC in the TCC forecast has a slight faster westward movement is related to the TC’s deep vertical development, and thus the TC movement is influenced by the strong westward steering flow above 500 hPa (figure not shown).

Although the track prediction is less sensitive to the assimilation strategy, the use of TC-centered assimilation has a major impact on the intensity forecast. As shown in Fig. 15, the TC in the TCC forecast went through a rapid intensification and has a lower MSLP and stronger maximum surface wind speed (MSWS) compared to the TC development in the CTL forecast. However, the TC in the TCC forecast is overintensified during the first two days, despite the fact that it reaches...
an intensity level close to the JTWC values afterward and sustains a longer mature stage similar to the observations. At 0000 UTC 17 September, the asymmetry with a stronger eastern sector remains in the SFMR observations (Fig. 16). The asymmetry of the TC is better represented in the TCC forecast compared to the CTL forecast, despite the wind speed around the eyewall being much stronger. Comparing the forecast SWS to the SFMR observations (Fig. 16), the gradient of the wind speed at the eyewall is generally better represented in the TCC forecast. The sharp decay in MSLP and MSWS 6 h earlier in the TCC forecast results from the faster movement of the TC. However, the decaying tendency agrees better with the observations since the landfall location is more accurately predicted.

In terms of the TC size defined by the radius of the 34-kt wind speed (Fig. 15c), the TC in the TCC forecast exhibits a size variation similar to that in the observations, while the CTL forecast has larger fluctuations, especially during the first 12 h. This is also related to the model spinup issue, as shown in the CTL track prediction. The TC in the TCC forecast generally has a smaller RMW (Figs. 16 and 15d); however, both forecasts cannot capture the RMW evolutions shown in the observations, which gradually decrease during 17 and 18 September and are related to the shrinking eye of an intensifying TC. As pointed out by Jin et al. (2014), this may be related to the fact that the horizontal resolution of 4 km may not be sufficiently high to maintain the size of the eye; higher model resolution is needed to represent the inner-core structure.

Although the TC in the TCC forecast is overintensified, error sources from the structure of the initial vortex and model uncertainty may add to the complexity of the intensity forecast. For example, interactions between the TC and ocean have not been considered in this work, and a cold eddy is observed right beneath the track of Fanapi on 17 September. (Mrvaljevic et al. 2013), possibly weakening the TC rapid intensification within the coupled atmosphere–ocean modeling framework. Nevertheless, results from Fig. 15 suggest that the TC in the TCC forecast goes through a dynamical development more similar to the observation than the CTL forecast. This may partially justify the adjustment made by the TC-centered data assimilation framework, which can be considered to provide a better dynamical structure to represent TC evolution. Further investigation with models with more complete physics...
and dynamics will help us better understand the intensification process.

7. Summary and discussion

This study investigates the impact of TC position uncertainty on ensemble-based TC data assimilation and prediction. We first demonstrate the concept of TC position error, uncertainty, and its effects on TC EDA within an idealized framework, which allowed us to identify the impact by varying the TC positions in terms of the distance from a reference storm center and the TC intensity. Based on a case study of Typhoon Fanapi (2010), we then examine the performance of a newly developed TC-centered regional EDA system coupled with the WRF Model. Dropsonde observations from the ITOP field campaign were used in the DA system, while the model analysis and forecasts of the TC structure are verified against independent surface wind measurements from the airborne SFMR and OSCAT satellite. Several key conclusions can be drawn from this study:

- Large TC position uncertainty has a major negative impact on the ensemble-based DA system, resulting in a less representative ensemble mean state through averaging and an ensemble-estimated background error covariance.
- TC-centered (TCC) regional EnKF DA can help alleviate the negative impacts of position errors by limiting position uncertainty and improving the TC structure in the ensemble DA system. The performance of 6-hourly analysis–forecast cycles is also improved significantly.
- The improved DA analysis in TCC had a positive impact on Fanapi track forecasts during the first 12 h by mitigating the model spinup issues as well as improving the landfall position at 72 h.
- The TCC DA impact on Fanapi intensity forecasts yielded mixed results. While the TC in the TCC forecast is overintensified during the first 2 days, it begins to resemble the JTWC best-track estimation afterward. The variations in TC structure from the TCC forecast generally agree better with the observations.

In the idealized scenarios, the results indicate that the position uncertainty can degrade the analysis performance as the position uncertainty becomes large. Assimilating an MSLP observation with large position spread in the background ensemble can create a large innovation due to the weak background mean TC. Also, this assimilation gives a false intensity adjustment with a strong and broad horizontal-scale correction, because of the unrealistically large and broad-scale ensemble spread over the inner core of the TC. Furthermore, if the background mean TC has a position error, although assimilating an MSLP observation is able to correct the TC position, an unrealistic asymmetric component will be introduced into the TC structure. The larger the position uncertainty, the larger the correction to the TC position; on the other hand, this creates a stronger asymmetric component. This artificial inner-core structure also limits the accuracy of the TC analysis and affects the intensity prediction, as expected. In comparison, when the position spread and error are small, the intensity uncertainty becomes noticeable, and observations can be better used to correct the intensity error with storm-scale features. Therefore, these results suggest that the TC position uncertainty and error should be first taken care of before assimilating observations for storm-scale corrections.

FIG. 14. (a) The JTWC best-track data (black) at 0000 UTC 16–20 Sep and the 3-day model track forecasts initialized at 0000 UTC 16 Sep (solid line) and 17 Sep (dashed line) with the CTL (blue) and TCC (red line) analyses. Open circles mark locations at 0000 and 1200 UTC. (b) Forecast track error against JTWC best-track data.
Using a case study of Typhoon Fanapi (2010), the CTL and TCC experiments were conducted to employ the conventional and the TC-centered WRF-LETKF systems, respectively. CTL can be considered to be the case with a large position uncertainty and error (P30I2) under the second scenario in the idealized experiment, while TCC is the case with a small position uncertainty and error (P5I2) under the first scenario. The TCC framework constrains the position error and minimizes the position uncertainty, which leads to a stable analysis performance with an improved TC inner-core structure. Also, MSLP observations are used more effectively to fine-tune the TC since the QC procedure rejects fewer observations. In contrast, the position error in the CTL analysis is reduced mainly with the help of the dropsonde data collected during ITOP. With the large position uncertainty, the TC in the CTL analysis at different times varies greatly from having large innovation and strong corrections, depending on the availability of the observations around the TC area. Furthermore, the TC in the TCC analysis has a better resemblance to the SFMR surface wind observations (RMSD of 4.2 m s$^{-1}$) than the TC in the CTL analysis (RMSD of 5.3 m s$^{-1}$). This reinforces the advantage of using the TC-centered DA.

The TC-centered approach has a larger impact on the TC intensity forecast than the track forecast, based on the 3-day forecasts initialized from the CTL and TCC analyses at 0000 UTC 16 September. Both the CTL and TCC forecasts demonstrated comparable and good track predictions with track errors at 72 h smaller than 100 km. However, in the CTL experiment, the strong corrections cause an imbalance between the model dynamic and analysis corrections and introduce a significant adjustment in TC movement and development during the first 12-h forecast, particularly degrading the track prediction and creating large variations in TC size. In comparison, the TCC analysis provides conditions favorable for TC development. In terms of intensity, the TC in the TCC forecast quickly intensifies and reaches
an intensity similar to the JTWC values. Although the peak wind is overpredicted, the inner-core structure in the TCC forecast is closer to the observations than the one derived from the CTL forecast. These results suggest that the TC-centered EnKF framework can improve the intensity prediction by refining the inner-core structure.

Although TCC has shown overall improvement on TC forecasts, there are some mixed results in intensity forecasting; for example, the TC intensity in TCC has been overestimated during the first two days of the forecast but becomes close to the observations afterward. These results indicate the difficulties in TC intensity prediction. As discussed in many previous studies, the evolution of TC intensity is a complicated process involving various factors, and the errors associated with these factors make numerical simulation and prediction very challenging. The accuracy of the initial conditions of the TC structure is only one of the factors; others such as the model physics (Tao et al. 2011) and dynamics (Jin et al. 2014) also play important roles. In addition, Typhoon Fanapi was affected by a preexisting oceanic cold eddy on 17 September (Mrvaljevic et al. 2013), which is the second day of our forecast, and the results presented in this study have not yet considered the effects of air–sea coupling on TCs, as shown in Chen et al. (2013) and Lee and Chen (2012, 2014). This may also partially explain why an initial TC with accurate intensity ends up being overestimated during the forecast.

We should point out that the results presented in this study are from the first real case study implementing the TC-centered DA framework, which was proposed by NH14, in an ensemble-based high-resolution TC assimilation and prediction system. The experiment and verification with independent observations of Typhoon Fanapi (2010) have shown that the TC-centered framework provides a positive impact on the TC analysis, especially for the inner-core structure. Although the effects of TCC on TC assimilation are clearly demonstrated, a question remains unanswered in this study as to whether a TC with different characteristics, such as intensity, size, and verticality, will affect the feasibility of TCC. We acknowledge that a case study may not be enough to prove that the TCC approach would be beneficial for all different kinds of TCs. However, as we demonstrated in our idealized study, large TC position uncertainty will dominate the results of the TC assimilation, indicating that no matter the characteristics of the TC, the position uncertainty is a first-order problem that we should take care of before conducting high-resolution TC assimilations. Except for the results shown in this study, the idealized study of NH14 also showed that their storm-centered
assimilation DA framework has delivered better performance compared to the conventional EnKF when the TC is tilted. To further explore the impacts of the TCC approach, our next step is to systematically investigate the capability of this newly developed regional EDA system with more real TC cases.

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