Assimilation of Tropical Cyclone Track and Wind Radius Data with an Ensemble Kalman Filter

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ABSTRACT

Improving tropical cyclone (TC) forecasts is one of the most important issues in meteorology, but TC intensity forecasting is a challenging task. Because the lack of observations near TCs usually results in degraded accuracy of the initial fields, utilizing TC advisory data in data assimilation typically has started with an ensemble Kalman filter (EnKF). In this study, TC minimum sea level pressure (MSLP) and position information were directly assimilated using the EnKF, and the impacts of these observations were investigated by comparing different assimilation strategies. Another experiment with TC wind radius data was carried out to examine the influence of TC shape parameters. Sensitivity experiments indicated that the direct assimilation of TC MSLP and position data yielded results that were superior to those based on conventional assimilation of TC MSLP as a standard surface pressure observation. Assimilation of TC radius data modified the outer circulation of TCs closer to observations. The impacts of these TC parameters were also evaluated by using the case of Typhoon Talas in 2011. The TC MSLP, position, and wind radius data led to improved TC track forecasts and therefore to improved precipitation forecasts. These results imply that initialization with these TC-related observations benefits TC forecasting, offering promise for the prevention and mitigation of natural disasters caused by TCs.

1. Introduction

Tropical cyclones (TCs) often cause torrential rainfall and strong winds that result in flooding, landslides, and even storm surges. Forecasting of TCs is an important meteorological tool for preventing and mitigating these natural disasters. Forecasts of TC tracks have steadily grown in accuracy with the development of numerical weather prediction (NWP) models, data assimilation schemes, satellite observations, and improved remote sensing equipment. However, TC intensity forecasting has not shown comparable advances and remains a challenging issue (Rappaport et al. 2009). The resolution and physical processes of NWP models are still insufficient to fully resolve and express the evolution of TCs. Another critical point hampering TC forecasting is the initialization step in NWP models.

NWP models are initialized through data assimilation processes in which the most probable atmospheric states are estimated by combining information from previous NWP model outputs and available observations. Given that observation data represent the true state with statistically constant errors, the quality of analyzed fields after data assimilation depends strongly on the availability of observations. However, TCs spend most of their existence over the ocean where observation data are usually scarce; thus, the initial fields of NWP models usually have large uncertainties near TCs. The lack of observations near TCs is a key problem for TC initialization.

To compensate for this problem, the TC bogus method has been used to modify the position and intensity of TC vortices. Bogus vortex profiles are constructed on the basis of statistical formulas and available observations, and then are incorporated into the initial fields of NWP models (Ueno 1989, 1995; Leslie and Holland 1995; Wang 1998). Although this scheme prepares dynamically and thermodynamically consistent initial vortices that are compatible with the resolution, dynamics, and physics of NWP models (Zou and Xiao 2000), it may include imbalances in the model and exclude observational information around TCs that has accumulated during previous data assimilation cycles.
With the development of sophisticated data assimilation techniques such as three- and four-dimensional variational data assimilation (3DVAR and 4DVAR, respectively), as well as the ensemble Kalman filter (EnKF), bogus profiles tend to be assimilated as a set of simulated observations. Zou and Xiao (2000) proposed the bogus data assimilation (BDA) scheme based on the 4DVAR framework, which derives simulated surface pressure data from bogus profiles for assimilation. Since Zou and Xiao (2000) demonstrated the usefulness of BDA for the simulation of the mature stage of Hurricane Felix (1995), many studies (e.g., Xiao et al. 2000, 2006; Pu and Braun 2001; Park and Zou 2004; Wu et al. 2006) have used it to initialize TC vortices. Pu and Braun (2001) and Wu et al. (2006) conducted sensitivity experiments to explore the potential impact of different variables on the BDA scheme and concluded that the wind field was more critical than the surface pressure field for maintaining the vortex structure. However, because the bogus scheme assumes a typical structure for TCs, the discrepancy between actual TCs and these artificial data may be large, especially in the generation and extratropical transition stages of TCs.

Satellite observations, given their availability over the ocean, have been effective in improving the initial conditions for TC forecasts. Surface wind measurements by scatterometers such as the European Remote Sensing Satellite (ERS) and QuikSCAT have been shown to have a positive impact on TC forecasts (Isaksen and Janssen 2004; Chen 2007). The Atmospheric Infrared Sounder (AIRS), version 5, retrieval product has been used to improve analysis fields and subsequent model forecasts for TCs, particularly forecasts with longer lead times (Reale et al. 2009; Miyoshi and Kunii 2012b). Assimilation of global positioning system (GPS) radiolocation soundings led to a successful simulation of the generation of Typhoon Usagi in 2007 (Kunii et al. 2011). More recently, the influence of assimilating geostationary satellite–derived atmospheric motion vectors was investigated by Wu et al. (2014). Another strategy for vortex initialization was proposed by Chen and Snyder (2007), in which vortex position information is assimilated with an EnKF. Because the EnKF can assimilate observations without an adjoint of the observation operator in contrast to 4DVAR, only a forward operator to find a TC position from the first guess is required to assimilate position information. TC minimum sea level pressure (MSLP) information can also be assimilated directly by comparing TC MSLP included in TC advisories to the MSLP estimated from the first guess. Note that the direct assimilation of TC MSLP is a different approach from treating MSLP estimates as regular sea level pressure (SLP) measurements obtained at the center of TCs. Chen and Snyder (2007) also showed that assimilating vortex shape is feasible with a simple two-dimensional barotropic model. Compared with satellite observations, assimilating the intensity, position, and shape information of TCs can be expected to modify dynamical fields more directly and with relatively smaller measurement errors.

In the current study, motivated by Chen and Snyder (2007), TC MSLP, position, and shape data were assimilated with a realistic NWP model. Although many previous studies have investigated the impacts of TC MSLP and position (e.g., Torn and Hakim 2009; Torn 2010; Wu et al. 2010; Kleist 2011), the use of TC shape in data assimilation studies is in an early stage. Moreover, TC position and central pressure have been treated as standard SLP observations in some studies (e.g., Hamill et al. 2011; Xue and Dong 2013). Thus, it would be valuable to compare the impacts of different strategies of assimilating TC parameters. The present study investigated the impacts of TC MSLP, position, and shape data on TC forecasts with an EnKF data assimilation scheme implemented within a limited-area atmospheric model. TC-related observations were based on the best-track estimates of the Japan Meteorological Agency (JMA).

This paper is organized as follows. Section 2 describes the assimilation of the TC-related observations. The experimental system and settings are described in section 3, the results are presented in section 4, and the conclusions are discussed and summarized in section 5.

2. Assimilation of tropical cyclone track and wind radius data

a. Ensemble Kalman filtering

In traditional Kalman filtering (Kalman 1960), the background model state vector $\mathbf{x}^{b}$ is updated to the analysis state vector $\mathbf{x}^{a}$ by

$$\mathbf{x}^{a} = \mathbf{x}^{b} + \mathbf{K} (\mathbf{y}^{o} - \mathbf{Hx}^{b}) \quad \text{and} \quad \mathbf{K} = \mathbf{P}^{b} \mathbf{H}^{T} (\mathbf{H}^{T} \mathbf{P}^{b} \mathbf{H}^{T} + \mathbf{R})^{-1},$$

where $\mathbf{y}^{o}$ is the observations, $\mathbf{K}$ is the Kalman gain matrix, and $\mathbf{H}$ is the observation operator matrix. The Kalman gain matrix is defined by using a background error covariance matrix $\mathbf{P}^{b}$ and an observation error covariance matrix $\mathbf{R}$. Because the brute-force application of the original Kalman filter to realistic NWP models is computationally prohibitive, atmospheric and oceanic data assimilation studies have used the EnKF, in which the Kalman gain matrix in Eq. (2) is approximated by using sample covariances composed of a finite number of ensemble forecasts.
The EnKF has an advantage in being able to use nonlinear models for the time evolution of the background error covariance because the matrix can be updated by using forecast ensemble perturbations alone. The fact that neither the tangent linear model nor its adjoint is therefore required in the EnKF enhances its flexibility in applications to various NWP models. Moreover, flow-dependent estimates of the background error covariance can be applicable in the EnKF. Because variational data assimilation schemes such as 3DVAR and 4DVAR generally use static background error covariance, analysis increments cannot reflect the background flow dynamics. Even in 4DVAR, which implicitly evolves error covariance, the flow dependency is limited, owing to its initialization with the static covariance at the beginning of each assimilation window. Hamill et al. (2011) demonstrated clear differences in analysis increments between the EnKF and 3DVAR, and pointed out that the EnKF should be particularly helpful with TC initialization, where the isotropic background error covariances commonly used in variational methods tend to be inappropriate.

Although using flow-dependent background error covariance would be ideal for data assimilation, especially for TC cases, the fact that the matrix estimated by a limited number of ensembles contains a sampling error degrades the accuracy of the analysis fields. In addition, the small number of ensemble members tends to lead to the underestimation of the background error covariance (Lorenc 2003). The covariance underestimation in turn generally leads to the underestimation of the observation weight, eventually resulting in divergence of the filter. To deal with these problems, the EnKF generally employs covariance localization and inflation schemes, but these require special attention because they can induce an imbalance in the system.

b. Assimilation of TC MSLP and position data

The TC MSLP and position can be obtained from the JMA best-track estimates. These parameters, along with the 30-knot (kt; 1 kt = 0.51 m s\(^{-1}\)) wind radius, are used by the JMA to produce TC bogus profiles (Ueno 1995). The BDA scheme has been adopted in the JMA operational regional and global analyses, in which the MSLP information in the best-track data is assimilated as a standard SLP observation. Some previous studies treated SLP observations derived from TC advisory data in a similar way (e.g., Hamill et al. 2011; Xue and Dong 2013) and showed that assimilating SLP observations at a TC center helped correct not only TC intensity but also position errors in analyzed fields.

In contrast, Chen and Snyder (2007) proposed a direct assimilation method of TC MSLP and position data throughout an EnKF by using an observation operator that was defined as an algorithm to identify a TC center and its maximum vorticity. This is quite a different approach from that previously described because it affects the TC structure itself, not only specific variables around a certain grid point, as has been the case with conventional observation data. Therefore, directly assimilating TC MSLP and position can be expected to have two essential effects: changing intensity and moving a vortex. However, model fields are affected through correlation between these TC parameters and control variables in the EnKF, so there is a concern that the expected analysis increments may not be obtained because of sampling errors caused by using a finite number of ensemble members.

In this study, the TC MSLP information is directly assimilated in a way similar to that proposed by Chen and Snyder (2007). The observational operator finds a TC center by determining the grid point where the SLP takes the minimum value within a grid box (200 km \(\times\) 200 km) centered at an observed TC position. The algorithm also interpolates SLP fields by fitting a quadratic curve and then returns MSLP information as well as the TC position in latitude–longitude coordinates. As mentioned previously, the fact that the use of an adjoint of the observation operator is not required in the EnKF facilitates the assimilation of these TC parameters.

c. Assimilation of TC wind radius data

As for parameters prescribing the TC shape, Chen and Snyder (2007) assimilated the major and minor axes of a vortex along with its rotation angle by fitting an ellipse to the isoline for half the value of the maximum vorticity. They retrieved these shape parameters by using an elliptical Fourier descriptor method. They verified the efficacy of the method with a simple two-dimensional barotropic model, but it is not straightforward to apply this approach to realistic TC cases. The current study uses a simpler measure of vortex size based on 30-kt wind radii at azimuth angles corresponding to the directions of the longest and shortest radii of winds specified in the JMA best-track estimates. That is, the observation operator to assimilate wind radius information finds a radius at a specific angle from a TC center where the wind speed is estimated to exceed a certain threshold. Because assuming an asymmetric TC structure causes the directions of the longest and shortest radii in the JMA best-track data to be generally opposite each other, essentially two observations related to the vortex shape are treated in this procedure. Although this approach does not allow direct modification of vortex shapes, it can utilize information included in the JMA best-track data without any further assumptions and thus avoid a source of conversion errors in the vortex shape observations.
3. Experimental design

a. The NHM–LETKF system

The local ensemble transform Kalman filter (LETKF; Hunt et al. 2007) is employed here for data assimilation as a representative of EnKF applications. The LETKF is classified as an ensemble square root filter (SRF), which generates an analysis ensemble mean and covariance that satisfy the Kalman filter equations for linear models (Kalnay 2010). In contrast to other SRF schemes, the LETKF updates the analysis at each grid point independently by simultaneous assimilation of a localized observation volume centered on a grid point. This feature considerably enhances parallel processing efficiency and therefore has facilitated applications of the LETKF to data assimilation studies (e.g., Miyoshi and Aranami 2006; Kang et al. 2011; Greybush et al. 2012; Miyoshi and Kunii 2012a; Yang et al. 2012, 2013; Penny et al. 2013). Miyoshi and Kunii (2012a) implemented the LETKF with the Weather Research and Forecasting (WRF) Model (Skamarock et al. 2005) and showed promising results with the analyses and forecasts for the case of Typhoon Sinlaku in 2008. The WRF–LETKF has also been applied to investigate the impacts of the AIRS retrievals (Miyoshi and Kunii 2012b) and the consideration of SST uncertainties in the EnKF (Kunii and Miyoshi 2012) on TC forecasts. Kunii (2014) coupled the LETKF with the regional nonhydrostatic model (NHM) of the JMA (Saito et al. 2006, 2007; Saito 2012) and discussed the predictability of local heavy rainfall by data assimilation as well as ensemble forecasting by using the NHM–LETKF.

In this study, an NHM–LETKF composed of 50 ensemble members was employed with configurations similar to those of Kunii (2014). The NHM was set up in the northwestern Pacific region with 241 × 193 grid points with a horizontal grid spacing of 15 km and 50 vertical levels reaching 22 km (Fig. 1). The specification of the NHM included a modified Kain–Fritsch convective parameterization scheme (Ohmori and Yamada 2006) along with three ice bulk cloud microphysics (Ikawa and Saito 1991) and the Mellor–Yamada level-3 closure model (Nakanishi and Niino 2004, 2006) for the turbulent scheme. Lateral boundaries for the NHM ensemble forecasts were supplied from JMA global model outputs. To account for lateral boundary uncertainties, perturbations derived from the JMA operational 1-week ensemble prediction system were added following Saito et al. (2012) in every data assimilation cycle. Consideration of the lateral boundary uncertainties in the assimilation cycles helps to prevent underestimation of the ensemble spread near boundaries, which may lead to filter divergence (Kunii 2014).

The LETKF assimilated observations from radiosondes, surface stations, pilot balloons, wind profilers, aircraft, and ships and buoys, as well as satellite-based winds. These observations, rounded to the nearest hour in hourly bins, were assimilated every 6 h with the four-dimensional
LETKF approach (Hunt et al. 2004). Spatial covariance localization with a physical distance was adopted with localization parameters of 200 km horizontally and 0.2 ln coordinates vertically. To prevent underestimation of the background error covariance, the adaptive inflation scheme proposed by Miyoshi (2011) was implemented, in which multiplicative inflation factors were adaptively estimated at each grid point based on observation innovation statistics. The system analyzed three-dimensional zonal \( u \), meridional \( v \), and vertical \( w \) wind components; temperature \( T \); pressure \( p \); water vapor mixing ratio \( q_w \); and water–ice microphysics variables depending on the cloud microphysics scheme.

\subsection*{b. Data assimilation experiments with TC parameters}

The impact of TC-related observations was evaluated for the case of Typhoon Talas in 2011. The TC was generated at 0000 UTC 25 August over the sea west of the Mariana Islands and moved slowly northward as it steadily intensified. Its minimum central pressure reached 970 hPa at 1200 UTC 29 August, and Talas made landfall on Shikoku Island in Japan around 0100 UTC 3 September. Talas was notable not only for its slow speed but also for its large 30-kt wind radius with a relatively symmetric structure, reaching a maximum of 350 nautical miles (n mi; 1 n mi = 1.852 km, so that 350 n mi = 650 km) according to the JMA best-track estimate. Because this feature of the typhoon induced a prolonged period of moisture advection, the total precipitation from Talas exceeded 1000 mm across some areas of Japan.

Before conducting comprehensive data assimilation experiments using all available observations, sensitivity experiments were conducted to assess the overall impact of information on TC MSLP, position, and wind radius. The TC parameters were individually assimilated into the first-guess field for 0000 UTC 1 September 2011, which was derived from a control experiment (CTRL) in which the NHM–LETKF performed a data assimilation cycle for Talas without TC-related observations from 0000 UTC 15 August 2011. It should be noted that the sensitivity experiments were carried out only for one data assimilation window, not the cycle experiments. For the first guess, the error in the TC track was about 50 km in the 6-h forecast, but the forecast of TC intensity was in good agreement with observations. To emphasize the impact of the TC-related observations, it was assumed that the MSLP of the TC was deeper by 20 hPa than the actual estimate throughout the sensitivity experiments. According to Ito et al. (2015), the estimated TC MSLP forecast error by NHM at the initial time was about 7 hPa on average. Because the horizontal resolution of the NHM–LETKF in this study was the same as that of the data assimilation system used in Ito et al. (2015), the error of 20 hPa roughly corresponded to 3 times the standard deviation (3\( \sigma \)) of the mean TC MSLP error at the initial time. For the experiment examining the impact of assimilating the TC wind radius, it was also assumed that the observed 30-kt wind radius was 1.5 times the first-guess radius to isolate its impact. In addition, observation errors were adopted that were smaller than those used for the realistic application for Talas: 1.0 hPa for MSLP, 10 km for position, and 10 km for wind radius.

Here, six experiments were performed in addition to the NOOBS experiment conducted with no observation data as a baseline. The MSLP information was assimilated as standard SLP observations in the TCPO experiment, whereas the MSLP data were directly assimilated along with the position data in the TCIP experiment. An experiment named TCPCLE was carried out with a configuration similar to the TCPC experiment, but with a larger observation error to evaluate the imbalance induced by assimilating TC-related parameters. The individual impact of the direct assimilation of the MSLP and position information was evaluated in the TCIN and TCPO experiments, where the MSLP and position data were individually assimilated. To validate the usage of the horizontal localization setting of 200 km for assimilating TC-related parameters, experiments with different localization parameters were carried out. The impact of the wind radius information was estimated in the TCWR experiment. The experimental settings of the sensitivity experiments are summarized in Table 1.

After the sensitivity experiments, two data assimilation cycle experiments were performed in addition to the CTRL experiment. The difference between the sensitivity experiments above and these cycle experiments was that a single TC-related observation was only assimilated with relatively large innovation in the sensitivity experiments, whereas the cycle experiments used comprehensive observation data including TC-related parameters with larger observation errors. The first of the cycle experiments, the TCIP experiment, assimilated the best-track TC MSLP and position data from the JMA at intervals of 3 or 6 h. The time interval differed because the JMA analyzed the TC track and related parameters every 6 h, but issued TC advisories more frequently, such as at intervals of 3 or 1 h, depending on the TC location. For the case of Talas, 6-hourly data were available from 1800 UTC 23 August to 0600 UTC 31 August, and then TC parameters were analyzed every 3 h until Talas became an extratropical cyclone on 5 September. The second of these, the TCALL experiment, assimilated wind radius information simultaneously with the TC MSLP and position data. After the data assimilation cycles, the TC forecasts were verified based on extended NHM forecasts with 5-km horizontal resolution (hereafter 5-km NHM) that were initialized with the analyses from each experiment.
In previous studies, the observational errors for the TC MSLP and position derived from TC advisories ranged from 1 to 3 hPa and from 10 to 20 km, respectively (e.g., Torn 2010; Wu et al. 2010; Hamill et al. 2011; Xue and Dong 2013). Following these settings and considering the horizontal resolution of the NHM–LETKF, the current study assigned errors of 2.0 hPa, 20 km, and 18.52 km (10 n mi) to MSLP, position, and wind radius observations, respectively. As pointed out by Knaff et al. (2010) and Torn and Snyder (2012), the errors of these parameters inherently depend on the time evolution of a TC; however, constant observation errors were adopted here because Talas maintained its intensity at a similar level throughout the experimental period.

4. Results

a. Sensitivity experiments for TC MSLP and position

First, the impacts of the different strategies for the assimilation of TC MSLP and position were examined. When MSLP data were assimilated as a surface pressure observation with an observation error of 1 hPa in the TCPC experiment, the analysis fields had smaller errors in TC MSLP and position than those of the first guess. Although the simulated MSLP reached about 954.6 hPa in TCPC, which was comparable to the corresponding observation of 950 hPa, deformation of the pressure field can be seen near the TC center (Fig. 2b). This unnatural pressure pattern must have resulted from the assimilation of the MSLP data, because it was not observed in the first guess (Fig. 2a). In contrast, directly assimilating TC MSLP and position information in the TCIP experiment improved the sea level pressure field with reasonable analysis increments (Fig. 2c). Although the observation errors of MSLP and position were set at small values (1.0 hPa and 10 km, respectively), the analyzed TC MSLP was 959.5 hPa in TCIP, a relatively large discrepancy compared to the observations at 950 hPa.

Next, to ascertain the individual impacts of the MSLP and position information, the TC MSLP and position data were assimilated separately in experiments TCIN and TCPO, respectively. Figure 3 shows the analyzed SLP fields along with the analysis increments in each experiment. When only the TC MSLP information was assimilated, the intensity became closer to the observation without relocating the TC position (Fig. 3a). When TC position information was assimilated, positive and negative increments emerged on the southwest and northeast sides of the TC center, respectively (Fig. 3b). This pattern implies relocation of the TC position and indicates that the assimilation works as expected.

![Fig. 2](Unauthenticated | Downloaded 07/13/24 09:22 PM UTC) Horizontal distribution of the mean SLP (hPa; contour) at 0000 UTC 1 Sept 2011 in the (a) first-guess, (b) TCPC, and (c) TCIP analyses. Analysis increments of the SLP (hPa; color) are shown in (b) and (c). Crosses indicate the observed TC center.
Assimilating the TC parameters may introduce an imbalance into the initial conditions, as shown in Fig. 2b. To assess this imbalance, the root-mean-square of the second derivative of the surface pressure with respect to time was evaluated within 760 km of the observation point at 1-min intervals. The distance of 760 km is nearly equivalent to the influence radius of observations when the horizontal localization parameter was set to 200 km in the NHM–LETKF. Figure 4a shows the time series of the domain-averaged imbalance in subsequent forecasts that were initialized from the analysis in each experiment. The TCPC experiment resulted in a larger imbalance than the others, especially in the initial stage of the model integration. After reaching a maximum value of about $96 \times 10^{-2}$ Pa s$^2$ at the first time step, the imbalance decreased to an equilibrium value after approximately 80 min. The TCIP experiment resulted in a smaller value than TCPC, and it reached equilibrium within 60 min. Figure 4b shows the time evolution of the MSLP of Talas simulated in each experiment. The TCPC experiment resulted in a sudden increase and decrease of the MSLP just after the start of model integration, whereas the analyzed MSLP at the initial time was closer to the observation compared with the other experiments. These features are not seen in the TCIP experiment, consistent with the evaluation of the model imbalance in Fig. 4a.

These results show that assimilating the MSLP as a regular SLP observation may introduce a larger imbalance into the system. To assess the impact of the error setting for observations, an additional experiment (TCPCLE) was carried out with settings similar to those for TCPC, but with a larger observation error of 2.0 hPa. The TCPCLE experiment yielded an initial TC MSLP of 963.6 hPa, which was weaker than that yielded by the TCIP experiment. Nevertheless, the introduced imbalance was larger than that in TCIP (Fig. 4a), and, moreover, a sudden increase and decrease of the MSLP was observed near the initial time (Fig. 4b). In these sensitivity experiments, the TC position error in the first
guess was about 50 km, which probably caused the imbalance in the system in both TCPC and TCPCLE. This implies that direct assimilation of the TC MSLP and position information in TCIP yields robust results and indicates the potential to produce more realistic TC analyses with the EnKF.

b. Impacts of localization scales

In this study, the same localization scales were adopted for all observations. The localization settings were derived by a trial-and-error procedure with conventional observations, but these may not be optimal for TC-related observations. To check the validity of the localization setting for TC-related observations, sensitivity experiments were additionally carried out with different localization parameters of 100 and 400 km. Here, except for the horizontal localization settings, the same configurations were used as those in the TCPC and TCIP experiments listed in Table 1.

Figure 5 shows the evaluated imbalance and simulated MSLP with different localization parameters for TCPC and TCIP. For both experiments, the small localization parameter introduced a large imbalance into the system (Figs. 5a and 5c) and resulted in a weaker MSLP than the other experiments (Figs. 5b and 5d). This was probably due to the excessive localization limiting the influence of the observations. By contrast, the large localization of 400 km slightly improved the predicted MSLP, although a larger imbalance was introduced just after the initial time. This result suggests that the larger localization parameter might be more suitable for assimilating TC-related observations in the current model settings; however, in the following experiments, a horizontal localization of 200 km was still applied, even for the TC-related parameters. This is because a localization scale of 200 km showed the best performance without the TC-related observations, and moreover, the benefits of using the larger localization scale for the TC-related observations were limited.

c. Sensitivity experiments for TC wind radius data

The impact of TC wind radius information was evaluated by assimilating the data under a relatively small observation error and a large innovation in the TCWR experiment. Figure 6 shows the vertical cross section of the meridional wind component as well as the analysis increment taken in an east–west profile of Talas. Assimilating TC MSLP and position information led to intensified circulation near the TC center (Fig. 6a). The analysis increment of the meridional wind reached approximately 20 m s$^{-1}$ because the observed TC intensity...
was assumed to be 20 hPa deeper than that for the first guess. When the 30-kt wind radius information was assimilated, the increment showed large values where the meridional wind speed was around 30 kt ($\sim 15 \text{ m s}^{-1}$) in the analysis field, especially on the west side of the TC (Fig. 6b). Compared with the TCIP experiment, the analysis increment in TCWR was distributed around the outer circulation, the indication being that wind radius information broadens the 30-kt wind radius in the model, as expected.

d. Application of assimilating TC parameters for Talas

Based on the results of the sensitivity experiments, three cycle data assimilation experiments were conducted for the case of Typhoon Talas in 2011: the TCIP experiment, which directly assimilated TC MSLP and position information in addition to the observations usually used in the NHM–LETKF; the TCALL experiment, which incorporated 30-kt wind radius information along with the observations used in TCIP; and the CTRL experiment, which did not assimilate any TC-related observations. To reduce the model imbalance introduced by the assimilation of these observations, the observation errors were increased to 2.0 hPa for intensity, 20 km for position, and 10 n mi for the 30-kt wind radius.

Figure 7 shows the time evolution of the MSLP and maximum 30-kt wind radius of Talas in the analysis fields. The overall pattern of strengthening and weakening tendencies was well captured even without assimilating TC parameters (Fig. 7a). This was probably because Talas had a steady MSLP of around 970 hPa, with a relatively small pressure gradient, during the experimental period. Although Fig. 7a shows no notable difference for the TC intensity analyses, Fig. 7b indicates a consistent improvement in the maximum wind radius from adding the 30-kt wind radius information in data assimilation. Although all of the experiments had large errors around 1200 UTC 29 August, overall, TCALL showed the best correspondence with observations.
especially from 30 August to 3 September. The difference in the maximum wind radius reached more than 70 n mi at 0600 UTC 2 September in CTRL and TCIP, which was corrected appropriately in TCALL by the assimilation of wind radius information. Verifications for the surface wind components in the 6-h first-guess fields are listed in Table 2. Similar to the estimation of the 30-kt wind radius in the analysis, the TCALL experiment shows the minimum root-mean-square errors (RMSE) for the zonal and meridional wind components. Since further improvement can be observed in TCALL by adding 30-kt wind radius data compared with TCIP, the verification result indicates that the assimilation of TC shape data has the potential to improve TC wind forecasts.

Figure 8a shows the forecast track errors of Talas in the extended 5-km NHM initialized at 0000 UTC 1 September. By assimilating TC MSLP and position information, notable differences can be seen between CTRL and TCIP, particularly after 24 h. Additional assimilation of TC wind radius data in TCALL resulted in track forecasting better than that in TCIP, reducing the track error from 124 to 79 km in the 42-h forecast. Figure 8b indicates a consistent advantage in the forecast track error with the TC-related parameters averaged over six initial times from 1200 UTC 31 August to 1800 UTC 1 September. In CTRL, the initial position error was approximately 40 km, reaching 120 km after the 42-h forecast. With TC MSLP and position information in TCIP, the track error was consistently reduced. However, in this case, it is expected that the track improvement may just come from correcting the TC initial position because the improvement in TCIP remained virtually constant during the forecast period.

Table 2. Time-mean bias and RMSE of surface wind components over six initial times from 1200 UTC 31 Aug to 1800 UTC 1 Sep for the deterministic 6-h NHM forecasts initialized by the CTRL, TCIP, and TCALL analyses. Units are meters per second.

<table>
<thead>
<tr>
<th>Expt</th>
<th>$u$ Bias</th>
<th>$u$ RMSE</th>
<th>$v$ Bias</th>
<th>$v$ RMSE</th>
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<tbody>
<tr>
<td>CTRL</td>
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<td>3.32</td>
<td>4.67</td>
</tr>
<tr>
<td>TCIP</td>
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<td>1.35</td>
<td>3.33</td>
<td>4.57</td>
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<tr>
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<td>1.14</td>
<td>3.23</td>
<td>4.57</td>
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The fact that an additional experiment where only TC position data were included showed a result similar to the TCIP experiment (not shown) supported the conclusion that assimilating TC position data was more critical for the improvement in the track forecast for Talas.

When 30-kt wind radius information was added in TCALL, the track forecast generally improved over the experimental period. Although there seemed to be less improvement in the TC position at the initial times, the track errors steadily improved to about 40 km by the 42-h forecast. These results suggest that assimilation of TC MSLP, position, and wind radius information through the EnKF positively affects the TC structures in the model, leading to improvement in track errors.

Talas brought torrential rainfall over Japan mainly because of its slow-moving speed and large 30-kt wind radius. Figure 9 shows the 3-h accumulated rainfalls at 0300 UTC 2 September 2011 predicted by the subsequent 5-km NHM forecasts. Although strong rainfall of about 100 mm (3 h)$^{-1}$ was measured when Talas was approaching Japan, this rainfall was not captured in the CTRL experiment (Fig. 9a). By incorporating TC parameters in
the TC initializations, the rainfall forecasts were improved because of more accurate TC track forecasting. In TCALL, the intense rainfall corresponded well with the observations (Fig. 9d).

Figure 9 depicts a single case of rainfall forecasts for Talas with different observation datasets, but statistical verification was also conducted in terms of the threat score and bias score of 3-h accumulated rainfall, defined as

\[ \text{threat score} = \frac{H}{F + O - H} \quad \text{and} \quad (3) \]

\[ \text{bias score} = \frac{F}{O}, \quad (4) \]

where \( F \) and \( O \) are the numbers of points where the predicted or observed precipitation exceeds a certain threshold, respectively, and \( H \) is the number of successful predictions. These verification scores were evaluated using the JMA’s precipitation observations, based on rain gauge and radar data, for the period from 1200 UTC 31 August to 0000 UTC 3 September 2011.

Figure 10 shows the threat and bias scores for 12- and 24-h forecasts by 5-km NHM initialized from the LETKF analyses. In the 12-h forecast, the threat and bias scores were improved by assimilating TC MSLP and position information, although the threat score became comparable to that in CTRL for intense rainfalls. By adding the 30-kt wind radius observations, both scores were markedly improved, especially for moderate and intense precipitation. With the longer lead times of
the 24-h forecasts, the positive impact of TC parameters on the threat score became more obvious. A significant decline in the bias scores can be seen for intense rainfalls in CTRL. This dry bias was probably due to the slow-moving speed in NHM forecasts initialized from CTRL analyses, leading to the underestimation of precipitation brought by Talas. The bias score in TCALL also showed a tendency for underestimation, the indication being that more sophisticated strategies would be desirable for assimilating TC shape information.

5. Summary and discussion

TC-related parameters such as MSLP, position, and shape were assimilated by using the EnKF based on the JMA’s operational mesoscale model. The efficacy of these parameters on TC analyses and subsequent model forecasts was verified through sensitivity experiments as well as by a realistic application to the case of Typhoon Talas in 2011. In the sensitivity experiments, direct assimilation of TC MSLP and position information helped make the intensity change and displacement of the TC more consistent with the observations. In comparison to the assimilation of the TC MSLP as a standard SLP observation measured at the TC center, the direct assimilation of MSLP showed the efficacy of adjusting the TC intensity without introducing unnatural analysis increments. Furthermore, the direct assimilation of TC MSLP yielded improvements even at longer lead times, whereas the impact was lost for longer forecasts when the TC MSLP was treated as an SLP observation, as pointed out by Hamill et al. (2011). When the TC wind radius was assimilated, the circulation was modified such that the tangential wind velocity matched the observed wind speed, demonstrating a direct impact on the simulated TC structure distant from the TC center. The impacts of TC-related observations were also verified through a realistic application to the case of Talas. The results showed that TC MSLP, position, and 30-kt wind radius data helped improve TC track forecasts. Verification scores for precipitation were markedly improved by the TC parameters. These results imply that initialization with TC observations can contribute to the prevention and mitigation of natural disasters caused by TCs.

FIG. 10. (top) Threat scores and (bottom) bias scores in the (a),(c) 12- and (b),(d) 24-h NHM forecasts for 3-h accumulated rainfall initialized with the CTRL (red), TCIP (green), and TCALL (blue) analyses, averaged over 11 initial times from 1200 UTC 31 Aug to 0000 UTC 3 Sep.
An important issue in this study is that all observations were assimilated with the same localization scale. The results of sensitivity experiments with different localization scales imply that it might be effective to use larger localization parameters for TC-related observations. Although the optimal localization parameter would depend on the background states as well as model configurations, it might be effective to use a localization parameter for TC-related observations larger than the others by employing the successive covariance localization technique proposed by Zhang et al. (2009). Another key issue is that this study could not evaluate the impact of 50-kt wind radii because the JMA did not estimate the 50-kt wind radii for Talas in its best-track data. In addition, the horizontal resolution of the data assimilation system in the current study was 15 km, which would be inadequate to derive 50-kt wind radii from background model fields as well as resolve the inner-core structures of TCs. The results obtained here show that assimilating 30-kt wind radii mostly affected TC track forecasts rather than TC intensity forecasts. However, it is plausible that 50-kt wind radius data could contribute to TC intensity estimates by correcting the inner-core structures of TCs. Hence, the assimilation of 50-kt wind radius data with a higher-resolution data assimilation system is an important subject of future research for improving TC intensity forecasts.

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