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Uncertainty Analysis Using the WRF Maximum Likelihood Ensemble Filter System and Comparison with Dropwindsonde Observations in Typhoon Sinlaku (2008)

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Abstract: In this study, the maximum likelihood ensemble filter (MLEF) is applied to a tropical cyclone case to identify the uncertainty areas in the context of targeting observations, using the WRF model. Typhoon Sinlaku (2008), from which dropwindsonde data are collected through THORPEX Pacific Asian Regional Campaign (T-PARC), is selected for the case study. For the uncertainty analysis, a measurement called the deep layer mean (DLM) wind variance is employed. With assimilation of conventional rawinsonde data, the MLEF-WRF system demonstrated stable data assimilation performance over multiple data assimilation cycles and produced high uncertainties mostly in data-void areas, for the given tropical cyclone case. Dropwindsonde deployment through T-PARC turned out to occur inside or near the weak uncertainty areas that are identified through the MLEF-WRF system. The uncertainty analysis using the MLEF method can provide a guide for identifying more effective targeting observation areas.

Key words: Uncertainty analysis, maximum likelihood ensemble filter, ensemble data assimilation, targeting observation

1. Introduction

Targeting (or adaptive) observation is one of the rapidly growing hot research topics in numerical weather prediction (NWP) in recent years. It is a process that first collects additional observations in a timely manner in the regions that are highly sensitive (or high uncertainty in the analysis) to the improvement of the short term (24-72 h) forecasts and then properly assimilates the additional observations to obtain improved initial condition for the subsequent NWP forecasts. In the past decades, many targeting observation field experiments have been conducted, e.g., the Fronts and Atlantic Storm-Track Experiment (FASTEX; Joly *et al.*, 1999), the North Pacific Experiment (NORPEX; Langland *et al.*, 1999), and the Dropwindsonde Observations for Typhoon Surveillance near the Taiwan Region (DOTSTAR; Wu *et al.*, 2005). These field experiments were designed to further our understanding and to improve the effectiveness of using targeting observation to improve the NWP forecasts. The knowledge and experiences acquired from those field experiments and the subsequent scientific researches have greatly contributed to the advancement in targeted observation strategies related to both the mid-latitude frontal systems and tropical cyclones (TCs). Because of the importance of the targeting observation, it became an important component of various field experiments in The Observing System Research and Predictability Experiment (THORPEX; WMO, 2008), a 10-yr international research program under World Weather Research Programme (WWRP)/WMO aiming at improving the accuracy of 1 to 14 day weather forecasts.

It is important to note that not every observation has the same impact on the NWP forecasts. The impact highly depends on the information content of each assimilated observation and the data assimilation system itself. Consequently, it is highly desirable to obtain and use the high information content observation data that can improve the NWP forecast. Two common questions typically confront the planners who are involved in laying out the targeting observation strategy in the early stage of any given field experiments. First, which method(s) should they use to properly identify the so called sensitivity regions for the targeting observation? Second, what kind of data assimilation algorithm(s)/system(s) should they use to properly assimilate those additional targeted observations to improve the analysis, such that the assimilated additional observation data have a positive impact on the subsequent NWP forecasts? Two commonly used methods, such as ensemble and adjoint based methods to identify the sensitivity regions, have been developed and applied during several past field experiments (e.g., FASTEX, NORPEX and DOTSTAR). Various advanced data assimilation algorithms/systems, such as three-dimensional variational (3D-Var; Lorenc, 1997), four-dimensional variational (4D-Var; Le Dimet and Talagrand, 1986; Lewis and Derber, 1985; Rabier *et al.*, 1998; Park and Zupanski, 2003), ensemble Kalman filter (EnKF; Evensen, 1994) and maximum likelihood ensemble filter (MLEF; Zupanski, 2005), have been used to assimilate the additional observations in the some of the recent studies. Majority of the targeting observation studies have been associated with the mid-latitude systems (Park and Xu, 2009), although several of the recent studies started to address issues related to the TC targeting observation (Wu *et al.*, 2007; Park *et al.*, 2008).

Tropical cyclone (TC) is one of the extreme weather phenomena

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that may cause tremendous property and human losses. The accurate TC track and intensity forecasts are one of the ultimate goals of NWP. Steady and significant improvements in TC track forecasts have been achieved in the past few decades, while lesser progresses in TC intensity forecasts have been obtained. Those continuous improvements are a consequence of many factors, including the increase of conventional, in-situ and satellite observations, improvement of the forecast models, advance in data assimilation methods, and development of intelligent targeted observing strategies. Among all the observations, satellite observations may have important global contribution to the overall analysis improvements, while the in-situ data from aircraft and the dropwindsondes may have the largest impact on the forecasts in the targeted area (Fourrié *et al.*, 2006). In recent studies, dropwindsonde data collected inside and around TCs have been proved to exert positive impact on the TC track forecasts (Burpee *et al.*, 1996; Tuleya and Lord, 1997; Aberson and Franklin, 1999; Wu *et al.*, 2007; Park *et al.*, 2008). Despite these progresses in the TC forecasts, there are still many scientific and practical issues related to various aspects of TC research and forecasts. Consequently, a new multi-national field campaign, THORPEX Pacific Asian Regional Campaign (T-PARC), was conducted in 2008 to addresses the shorter-range dynamics and forecast skill of the eastern Asian and the western North Pacific region and its downstream impact on the medium-range dynamics and forecast skill of another region (in particular, the eastern North Pacific and North America). The field phase of T-PARC was designed to leverage multi-national efforts to address these two overarching foci. While T-PARC encompasses varying time and space scales, the primary objectives of each region are the same (i.e., to increase under-standing of the mechanisms that will lead to improved predictive skill of high impact weather events). This multi-scale approach of T-PARC is desirable as high impact weather events over these two regions have strong dynamical links (see more details in NCAR, cited 2009). The availability of additional observations obtained from the targeting observation presents a great opportunity to develop and test a new strategy for targeted observations and data assimilation which would improve the predictions of TC.

The objectives of this study are twofold. The first is to examine the potential of using an ensemble data assimilation method, known as the MLEF that was originally proposed by Zupanski (2005) and Zupanski and Zupanski (2006), in the context of the targeting observation. The second is to examine a relatively new measurement of analysis uncertainty, namely the deep layer mean (DLM) wind variance (Aberson, 2003), that is of great interest to the targeting observation in general. The DLM wind variance is a desirable measure for defining the TC targeted areas for deploying adequate observing systems (e.g., dropwindsondes), since it commonly defines these areas outside the cyclone center (Majumdar *et al.*, 2006; Reynolds *et al.*, 2007; Chou and Wu, 2008). Because our computer and data resources are limited, we only selected one TC case, Typhoon Sinlaku (2008), during the T-PARC.

In Section 2, we introduce a mesoscale data assimilation system. The synoptic situation of Typhoon Sinlaku is summarized in Section 3. The numerical experiment design is presented in Section 4. We show and discuss the numerical results in Section 5. Finally, in Section 6, the conclusions are drawn and further discussions are given.

2. Mesoscale data assimilation system

Since NWP is essentially an initial value problem, the initial condition greatly controls the outcome of the various aspects of the overall forecasts that include the TC track and intensity forecasts. While it is very important to use a good NWP model, it is equally crucial to employ an advanced data assimilation system to properly assimilate all the available observations including those obtained from the targeting observation. In this context, an advanced four-dimensional (4D) mesoscale data assimilation system is a good tool to incorporate the additional special observations.

There are two major components of a typical advanced 4D mesoscale data assimilation. One is the mesoscale prediction model itself that can be used not only to describe the dynamical evolution of the weather phenomena, but also to obtain information related to the flow-dependent error covariance required in 4D data assimilation. The other is the data assimilation algorithm that is used to find the best available analysis by optimally combining all *a priori* information using the prediction model as a dynamic constraint. The mesoscale prediction model used in this study is the NCAR Advanced Research WRF (ARW) model version 2.2 (Skamarock *et al.*, 2005), while the data assimilation algorithm employed here is a variant of the MLEF, known as the local MLEF (LMLEF) (Zupanski *et al.*, 2008b). We provide a brief overview of the mesoscale data assimilation system in the following.

a. Mesoscale NWP model

The ARW is a mesoscale community model that contains many options for physical/computational parameters. More details related to ARW, such as the governing equations, the numerical schemes, and physical packages, can be found in Skamarock *et al.* (2005). For applying to a TC case, we employed the WRF Single-Moment 3-class (WSM3) scheme (Hong *et al.*, 2004) for microphysics, a mass flux scheme (Kain, 2004) for the cumulus parameterization, and the YSU scheme (Hong *et al.*, 2004) for the planetary boundary layer. The surface layer physics scheme is based on the Monin-Obukhov similarity theory.

b. Data assimilation algorithm

There are two kinds of advanced 4D data assimilation algorithms, namely the variational and ensemble ones, commonly used in operational and research communities. There are quite a variety of variants within each type of the algorithm depending on the actual implementation. As we mentioned earlier, we use a special variant of MLEF, known as LMLEF, in this study.

The MLEF solves a non-linear data assimilation problem through an iterative minimization of a cost function. A Hessian preconditioning is employed in MLEF to speed up the convergence of the minimization of the cost function. As demonstrated in Zupanski (2005) and Zupanski *et al.* (2008a), the application of the Hessian preconditioning results in a mathematically correct solution (i.e., equal to the Kalman filter) after a single minimization iteration in linear data assimilation problems and brings about significantly improved minimization convergence in non-linear data assimilation problems.

The LMLEF and MLEF differ only in the way the error covariance localization was performed. Independent local domains are introduced in the covariance localization in LMLEF. The local domains are defined as rectangular sub-domains of the entire model domain, including contiguous model grid points. Notice that there is no sub-domain in the vertical. That is, each horizontal sub-domain extends through the entire vertical column of the atmosphere. The size of the sub-domains is determined by taking into account the scales of the atmospheric processes (e.g., the size of the TC). As a result, the data assimilation problem is first solved independently over each local domain. The final (global) solution is then obtained by combining the local solutions. An undesirable effect of solving the analysis problem over the independent local domains is, of course, a possible noise generation at the boundaries between the local domains. There are two possible methods to deal with this issue. This problem could be reduced by defining overlapping local domains (Ott *et al.*, 2004), and/or by applying a smoothing to the analysis weights (Yang *et al.*, 2009). There is no overlapping sub-domain in LMLEF. However, we do apply smoothing to the analysis weights (Yang *et al.*, 2009), which reduces the noise at the boundaries of the sub-domains. One of the advantages of using non-overlapping sub-domains is in straightforward calculations of information measures, such as degrees of freedom for signal (Rodgers, 2000; Zupanski *et al.*, 2007) or E dimension (Oczkowski *et al.*, 2005), since each observation belongs to a single local domain and thus contributes to the information measures uniquely (Zupanski, 2009).

Unlike the 4D variational data assimilation algorithm, there is no requirement for the tangent linear and adjoint models associated with the nonlinear mesoscale prediction model (ARW in this case) in the LMLEF 4D data assimilation system together. It is rather straight forward to put the LMLEF-ARW data assimilation together.

3. Case description

On September 7, 2008, Typhoon Sinlaku was initially forecasted not to intensify into a tropical depression within 24 hours. However, it was developed into a tropical depression early next morning. During the evening the depression had intensified into a tropical storm. Early on September 9, Typhoon Sinlaku up-

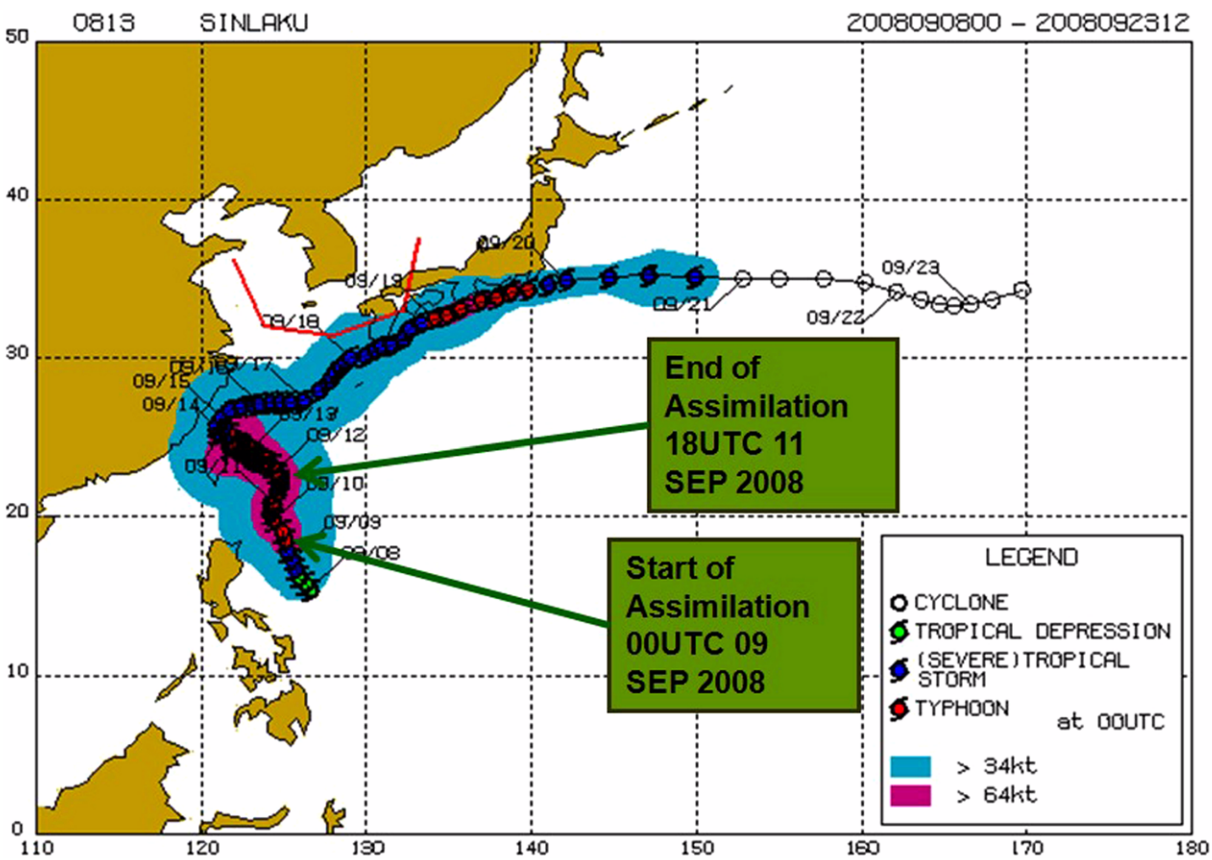

Fig. 1. The best track for Typhoon Sinlaku (2008). From the Typhoon Research Center, Kongju National University, Korea.

graded to a severe tropical storm at 560 km northeast of Manila in the Republic of Philippines on September 9, fast developing into typhoon later that day. Early on September 14, it is downgraded to a severe tropical storm and then early on September 16 it is downgraded again into a tropical storm whilst it moved closer to Japan. Early on September 21, it is downgraded to an extra tropical low as it moved further away from Japan. It made landfall at the southeastern coastal region of the Korean Peninsula around 0000 UTC 18 September (see the best track in Fig. 1). Sinlaku's maximum sustained winds increased to 173 km h^{-1} and a 24-hr accumulated rainfall on September 18 of 40.5 mm at Seogwipo, 49.5 mm at Jeju Island, and 50.5 mm at Wonju (not shown). In this study, numerical experiments are performed for the case of Typhoon Sinlaku (2008) from 0000 UTC 09 to 1800 UTC 11 September 2008.

4. Experimental design

a. Mesoscale model and ensemble data assimilation configuration

We use the ARW dynamical core with a horizontal resolution of 28 km and 30 vertical levels. We use 90 × 100 grid points in the horizontal domain that covers an area of 2,492 km × 2,772 km (Fig. 2). A time step of 1 min is used to integrate the model forward in time. The control variable includes u, v, z', θ, and q_{vapor}. We employ 32 ensemble members, thus the ensemble size is several orders of magnitude smaller than the size of the control variable. This reduction in number of control variables causes an unintended side effect. That is, the data assimilation system with reduced control variables is rank deficient (i.e., the degree of freedom of the system is very limited). One very effective technique to increase the degree of freedom is through the covariance localization. In this study the covariance localization is done through the local domains. With this localization, the number of degree of freedom in the data assimilation system is significantly increased. We employ the covariance localization using 3 × 3 = 9 sub-domains (see Fig. 2). Notice that we do not examine the impact of covariance localization on the outcome of the analysis in this study since it was examined in Zupanski *et al.* (2008b).

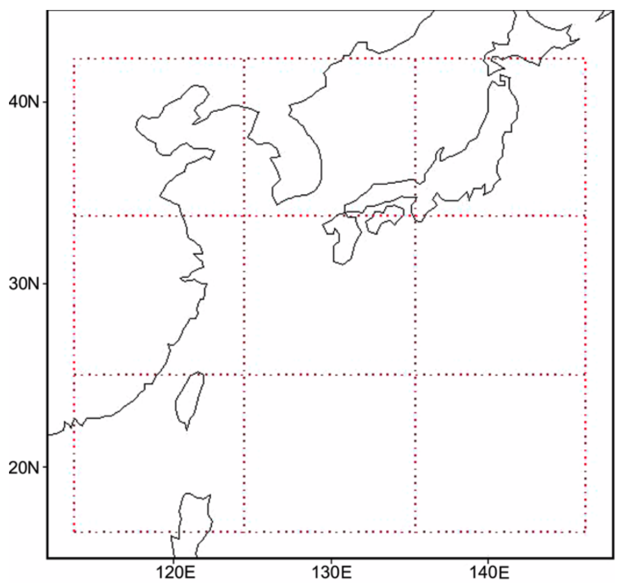

Fig. 2. Model and local domain for integration and covariance localization in the WRF-MLEF system.

b. Data assimilation set up

Typhoon Sinlaku (2008) spanned the period of 0000 UTC 09 – 0018 UTC 11 September 2008. To properly simulate and study the Typhoon Sinlaku, we choose to run a total of 12 data assimilation update cycles with each update cycle being a 6-h data assimilation window. To start the update cycle, we simply use the archived 1° × 1° resolution National Centers for Environmental Prediction Global Forecast System (NCEP GFS) analysis fields and generate the initial condition in the first data assimilation cycle by interpolating them to our model grid points. After the first data assimilation cycle, the analysis at the end of the previous cycle is used as the initial condition for the second data assimilation cycle. The procedure is continuous until it reaches the 12th cycle. Since ARW is a limited area model, it requires the lateral boundary conditions. It would be ideal if we have had access to a set of global ensemble forecasts that could have provided us with the perturbed lateral boundary conditions. To achieve the objectives set in this study, it is reasonable to use the lateral boundary conditions extracted from the NCEP GFS data set.

We use the time-shifted forecast technique as described in Zupanski *et al.* (2008b) to generate the initial ensemble perturbations. Although we could have used the commonly used random perturbation technique, the time-shifted ensemble perturbations reflect the model dynamics more realistically (Zupanski *et al.*, 2008b). Notice that the ensembles are initialized by time-shifted forecasts only in the first assimilation cycle. In all subsequent cycles the ensemble perturbations were defined by the standard ensemble-based covariance update (Zupanski *et al.*, 2008b). The analysis solution in each updated cycle is obtained after a single nonlinear iteration. Additional nonlinear iterations (similar to the outer loops used in 4D-Var algorithm) are not essential in this application since the observation operator used is approximately linear. Benefits of additional nonlinear iterations in non-linear applications were examined in more detail in Zupanski *et al.* (2008a).

5. Results

a. Filter stability

We have performed data assimilation experiments over 12 consecutive data assimilation cycles, covering the period from 0000 UTC 09 to 1800 UTC 11 September 2008. Examination of the results indicated a stable filter performance and a positive

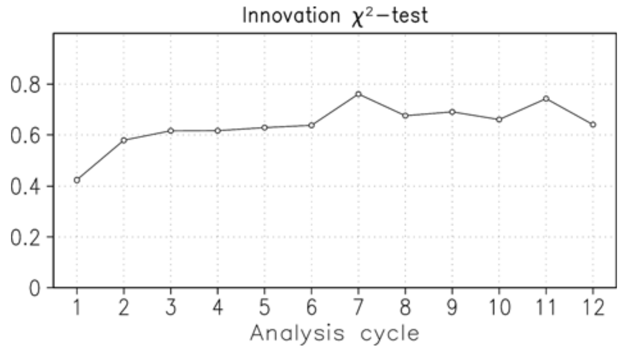

Fig. 3. The values of the χ^2 test statistics shown as a function of data assimilation cycles.

impact of data assimilation on the analysis and forecast of the typhoon. In Fig. 3, the χ^2 (chi-square) test results are shown for all 12 data assimilation cycles. Plotted are the mean squared values of normalized analysis innovations calculated over all observation points in a given data assimilation cycle. The normalized innovations are defined as differences, in observational space, between the observations and the analysis, normalized by the estimated analysis error (Zupanski, 2005). Assuming that the observational and forecast errors are Gaussian, the squared normalized innovations should follow the χ^2 distribution statistics with the mean equal to 1 and the variance equal to 2 (Dee *et al.*, 1995; and Menard *et al.*, 2000). Results in Fig. 3 indicate that the mean squared normalized innovations are different from 1, thus do not strictly follow the expected χ^2 distribution. This is because the WRF model is non-linear, which causes the forecast errors to depart from Gaussian. Nevertheless, important to note in Fig. 3 is that the chi-square values do not exhibit an increasing or decreasing trend with increasing data assimilation cycles, which is an indication of a stable filter performance.

b. Improvement of short term TC forecasts

In Figs. 4 and 5, examples of data assimilation impact on a short term (6 h) forecast, or background, are shown. The differences in the surface pressure (in hPa) between the experiment with and without data assimilation are shown, as functions of data assimilation cycles, in panels (a) through (k). Both experiments were initialized at the beginning of the first data assimilation cycle (0000 UTC 09 September 2008) using the same NCEP GFS analysis. In the subsequent cycles, the initial conditions were updated every 6 h in the experiment with data assimilation, while in the experiment without data assimilation

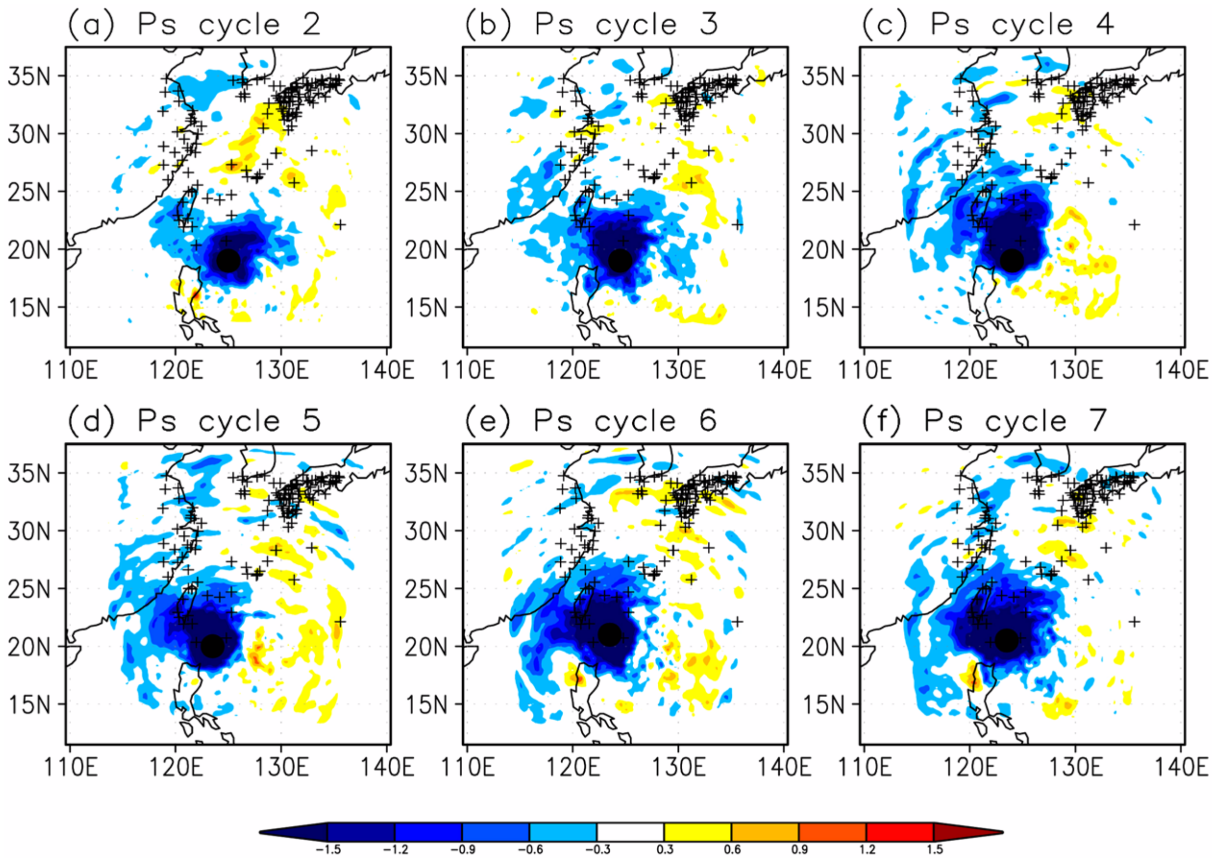

Fig. 4. Difference in the surface pressure (in hPa) between the 6 h forecast from the LMLEF and the "old" forecast from the experiment without data assimilation. Both experiments are initialized using the NCEP GFS analysis at the beginning of the first data assimilation cycle (at 0000 UTC 09 Sep 2008). The results are shown for cycles 2 through 7, in panels (a) through (f), covering time period from 0600 UTC 09 Sep 2008 to 1200 UTC 10 Sep 2008. The black circle indicates the observed location of the typhoon.

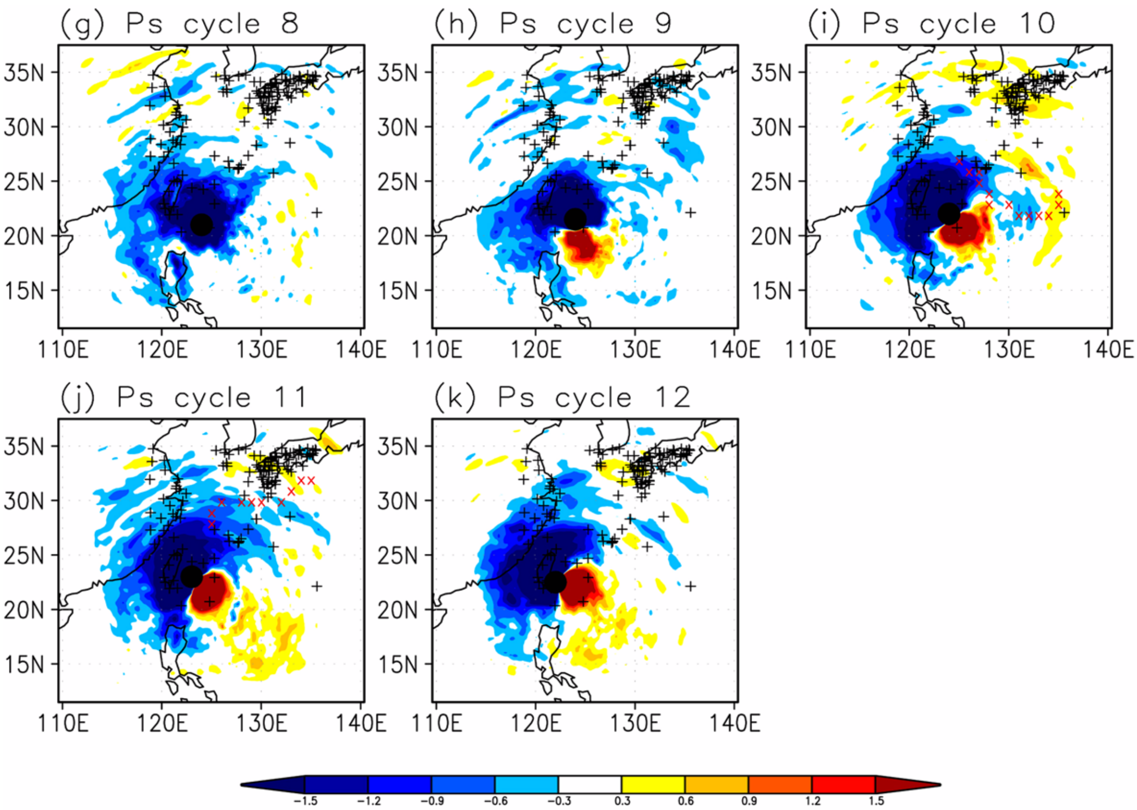

Fig. 5. Same as Fig. 4 but for cycle 8 through 12.

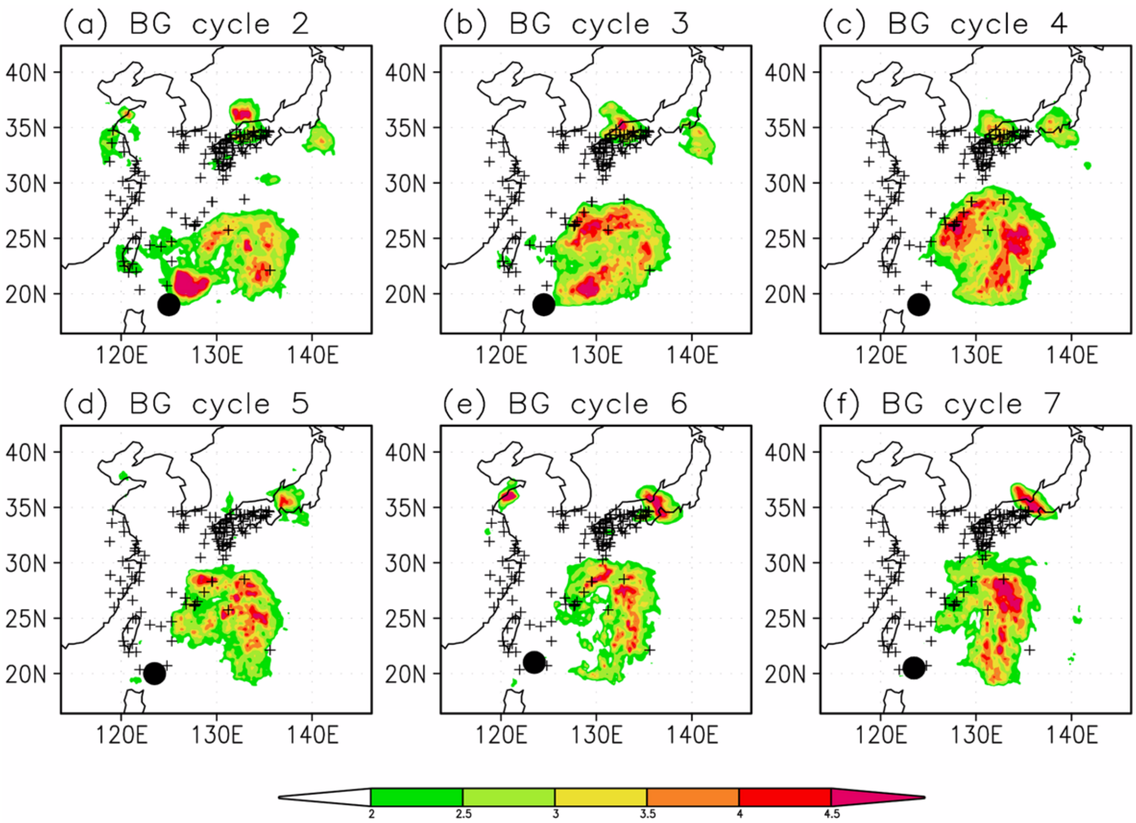

Fig. 6. Uncertainty of the 6 h forecast of the DLM wind intensity (in m s^{-1}), calculated as a square root of the DLM wind ensemble variance. Results from cycles 2 through 7 are shown in panels (a) through (f).

the "old" forecast is used. The results are shown only for cycles 2 through 12. We do not show the result from the first data assimilation cycle since this is considered a warm-up cycle.

As indicated in Fig. 4, there is a negative area in the surface pressure difference. The observed cyclone center (marked by a black circle) is typically found within the boundaries of the negative area. This is an indication of a positive impact of data assimilation in deepening the cyclone center toward more correct intensity. In Fig. 5, in the later cycles, there is a dipole (positive-negative) pattern in the surface pressure difference. This represents a positive impact of data assimilation in moving the cyclone center toward more correct location.

c. DLM wind uncertainty

In this subsection we pay special attention to the DLM wind uncertainty, since this is a measure often used to define the sensitivity areas for targeted observations. We calculate the DLM vector wind uncertainty over the 850-200 hPa deep layer according to the following formula

$$DLM\ uncertainty = \left\{ \frac{1}{Nlayers} \sum_{l=1}^{Nlayers} [(\sigma_u)_l^2 + (\sigma_v)_l^2] \right\}^{\frac{1}{2}} \quad (1)$$

Where σ_u and σ_v are the standard deviations (i.e., ensemble spread) of forecast errors for u and v wind components, index l denotes the model vertical layer and *Nlayers* is the number of model vertical layers in the deep layer. Note that the value obtained in Eq. (1) is a scalar, varying only in the horizontal (with the model grid points), thus it can be used for defining targeted areas in the horizontal plane.

The DLM wind uncertainty calculated for the background (6 h) forecast is plotted in Figs. 6 and 7, for data assimilation cycles 2 through 12 in panels (a) through (k), respectively. Note that, even though longer term forecasts (48-72 h) are typically used to calculate the DLM wind uncertainty in practical targeted observation applications, we use a considerably shorter forecast in this study in order to be able to easily compare the results from the multiple assimilation cycles. By examining Figs. 6 and 7 we notice contiguous areas of large DLM wind uncertainty. In addition, uncertainty areas with large magnitude DLM mostly occur in data-void areas. These areas are considered good candidates for targeted observations. Based on these results, the targeted areas would be defined away from the cyclone center and often to the northeast or southeast from the cyclone center. Other studies have also indicated similar characteristics of targeted areas based on the use of the DLM wind uncertainty (Aberson and Etherton, 2006; Wu *et al.*, 2007). In Cycle 10, dropwind-

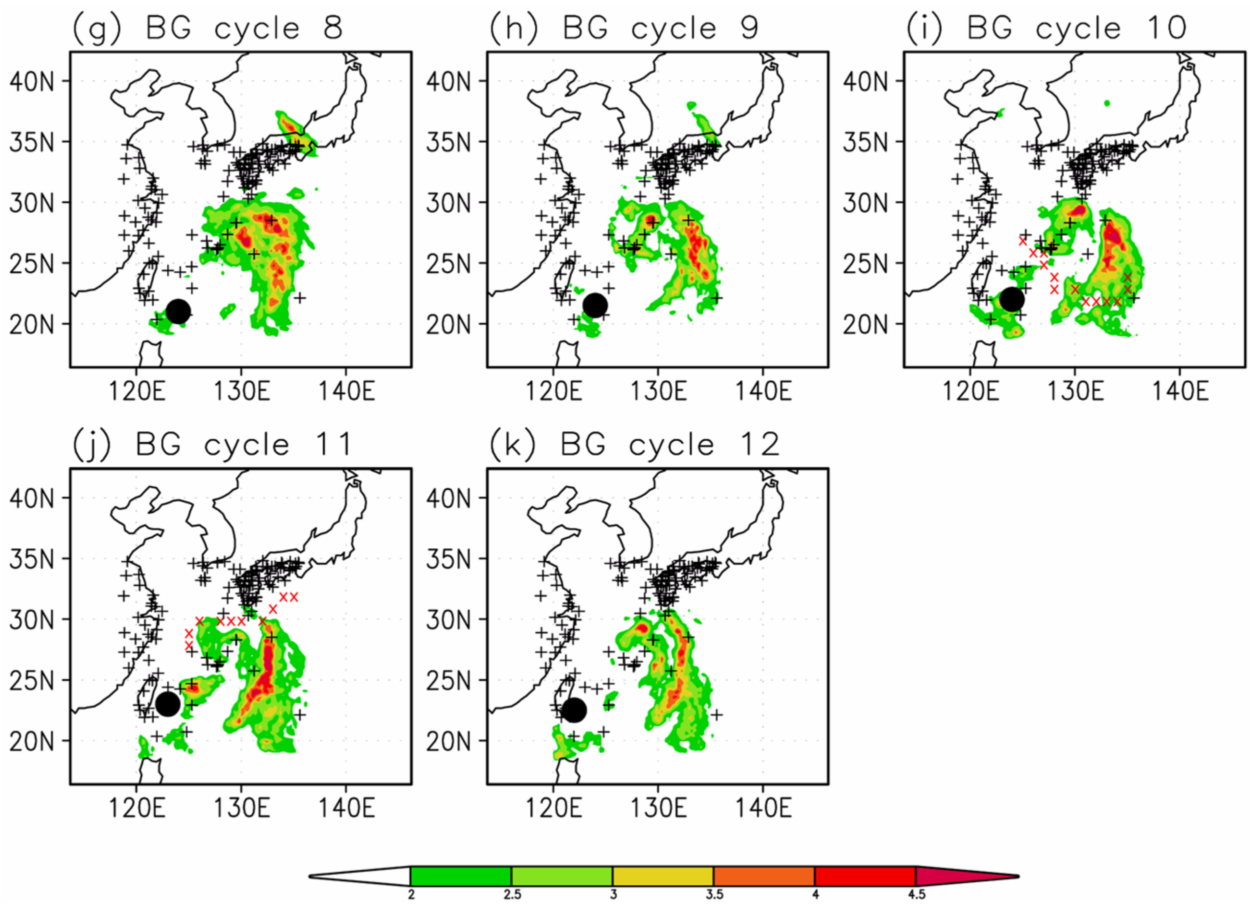

Fig. 7. Same as Fig. 6 but for cycle 8 through 12.

sonde data were available in the area of moderate uncertainty. Thus assimilation of such data may improve the forecast accuracy to some extent. In Cycle 11, dropwindsondes were deployed just near but outside of the uncertainty area; thus those data may not give significant improvement in forecast accuracy.

6. Conclusions

Initial experiments with MLEF using WRF model in typhoon forecast indicated stable data assimilation performance over multiple data assimilation cycles (e.g., in terms of chi-square tests). Analysis and forecast perturbations for Typhoon Sinlaku case reflect atmospheric dynamics – this is the impact of flow-dependent forecast error covariance. The observed cyclone center is typically found within the boundaries of the negative area in dipole, implying improvement of typhoon forecast both in intensity and location after assimilation. The results indicate promise for targeted observations strategies: the targeted areas would be defined away from the cyclone center and often to the northeast or southeast from the cyclone center, especially where observations are rare. Some dropwindsonde data were available in the area of moderate uncertainty.

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