Effect of Observation Network Design on Meteorological Forecasts of Asian Dust Events

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ABSTRACT

To improve the prediction of Asian dust events on the Korean Peninsula, meteorological fields must be accurately predicted because dust transport models require them as input. Accurate meteorological forecasts could be obtained by integrating accurate initial conditions obtained from data assimilation processes in numerical weather prediction. In data assimilation, selecting the appropriate observation location is important to ensure that the initial conditions represent the surrounding meteorological flow. To investigate the effect of observation network configuration on meteorological forecasts during Asian dust events on the Korean Peninsula, observing system simulation experiments using several simulated and real observation networks were tested with the Weather Research and Forecasting modeling system for 11 Asian dust events affecting the Korean Peninsula during a recent 6-yr period. First, the characteristics of randomly fixed and adaptively selected observation networks were investigated with various observation densities. The adaptive observation strategy could reduce forecast errors more efficiently than the fixed observation strategy. For both the fixed and adaptive observation strategies, the mean forecast error reduction rates increased as the number of assimilated observations and the distance between observation sites increased up to 300 km. Second, the effects of redistributing the real observation sites and adding observation sites to the real observation network based on the adaptive observation strategy were investigated. Adding adaptive observation sites to the real observation network in statistically sensitive regions improved the forecast performance more than redistributing real observation sites did. The strategy of adding adaptive observation sites is used to suggest the optimal meteorological observation network for meteorological forecasts of Asian dust transport events on the Korean Peninsula.

1. Introduction

Asian dust events are an important spring phenomenon in East Asia. Recently, the importance of predicting Asian dust events on the Korean Peninsula has been increased because of the increasing number of events (Sugimoto et al. 2003), the increasing occurrence frequency in fall and winter in South Korea (Kim et al. 2013), and the longer duration of individual events. To mitigate the social and economic damage from Asian dust events, accurate forecasts of such events are essential.

Numerical models for predicting Asian dust events were initially developed in the late 1990s. During the Asian Pacific Regional Aerosol Characterization Experiment (ACE-Asia; Huebert et al. 2003), the estimated vertical dust fluxes and elevated dust concentration layers varied across the different dust transport models (Uno et al. 2004; Liu et al. 2003; Gong et al. 2003) as a result of the varying surface wind speeds that were dependent on the model resolution, uncertainties in the surface land use and soil texture information, and the dust removal scheme. Liu et al. (2003) simulated Asian dust storms with a high-resolution regional dust model, and Uno et al. (2008) presented detailed three-dimensional structures of Asian dust outflow using a four-dimensional variational data assimilation (4DVAR) scheme with a dust transport model. However, as noted by Shao and Dong (2006), the uncertainties of the model predictions remain large despite the state-of-the-art dust models showing a certain capability in predicting the onset and evolution of Asian dust storms.

To accurately predict Asian dust, it is crucial to improve the quality of the initial conditions of both the
meteorological fields and the dust emissions because dust transport models require this information as input. In terms of the effect of meteorological forecasts on chemical transports, Sistla et al. (1996), Biswas and Rao (2001), Zhang et al. (2007), and Liu et al. (2011) showed that small uncertainties in meteorological input to transport models result in large uncertainties in ozone and CO₂ predictions. In this sense, the uncertainties in the meteorological forecasts could cause large errors in Asian dust forecasts on the Korean Peninsula (Kim et al. 2008; Kim and Kay 2010; Kim et al. 2013). The transport paths of Asian dust connecting the dust source regions to the Korean Peninsula are closely associated with extratropical pressure systems over East Asia (e.g., Chung and Park 1997; Uno et al. 2001; Kim et al. 2013). During Asian dust events on the Korean Peninsula, typically a high pressure system follows behind a surface frontal cyclone over the Korean Peninsula (e.g., Merrill and Kim 2004; Kim et al. 2008, 2013). Kim et al. (2008) showed that difficulties in forecasting the path of the dust and the location and speed of the high pressure system behind a surface frontal cyclone over the Korean Peninsula caused an incorrect forecast for the Asian dust event that occurred during 7–9 April 2006. In addition, Jhun et al. (1999) showed that the flow direction on the 850-hPa layer plays a crucial role in transporting Asian dusts to the Korean Peninsula. Murayama et al. (2001) and Kim et al. (2010) confirmed that most aerosols associated with Asian dust events observed in South Korea are located below 5 km in height. Therefore, in the present study, we focus on improving the meteorological forecasts of extratropical pressure systems and associated lower to midtropospheric flow directions over the Korean Peninsula during Asian dust events.

High-quality initial meteorological fields could be obtained by constructing an optimal observation network for atmospheric conditions during Asian dust events and using the observations obtained from this network to determine the initial meteorological conditions. To construct the optimal observation network for initial meteorological conditions and forecasts for Asian dust events, the characteristics of the observation network should be studied. Morss et al. (2001) and Liu and Rabier (2002) investigated the characteristics of observation networks based on the density of observation sites using a quasigeostrophic and one-dimensional model, respectively. However, no studies have considered the effect of the observation network for meteorological forecast fields specifically during Asian dust events using a realistic modeling system. In addition, although the Korea Meteorological Administration (KMA) collects meteorological and dust [e.g., particulate matter 10 (PM10) concentration] data from surface observation sites operated by the KMA and the China Meteorological Administration (CMA) over the Asian dust source regions, these sites were determined subjectively, and the observational data are insufficient to produce accurate Asian dust predictions (Kim et al. 2008, 2013). Therefore, to determine an optimal observation network for meteorological forecasts during Asian dust events, the characteristics of observation networks were investigated for 11 Asian dust events that affected the Korean Peninsula from 2005 to 2010 by performing observing system simulation experiments (OSSEs) using the Weather Research and Forecasting (WRF) Model. First, the characteristics of randomly fixed and adaptive observation networks were investigated for various observation densities and distances between observation sites. Adaptive observation strategies are used to design the observation network because they employ more objective criteria to decide observational sites, which improve meteorological transport forecasts associated with Asian dust events, as mentioned in Kim et al. (2013). The adaptive observation networks were determined according to adjoint sensitivity analyses. The characteristics of adjoint-based forecast sensitivity for Asian dust events have been investigated by Kim et al. (2008), Kim and Kay (2010), and Kim et al. (2013), which found that adjoint-based forecast sensitivity is a beneficial tool for determining observation sites and improving the meteorological forecasts of Asian dust events on the Korean Peninsula. Kim et al. (2013) showed that the linearity assumption holds well for meteorological forecasts of 46 Asian dust occurrences from 2005 to 2010. Second, two experiments with the modified real observation network (i.e., radiosonde sites) were performed to determine an optimal observation network. Modifications to the real observation network were performed either by redistributing observation sites within the real observation network or by adding adaptive observation sites to the real observation network. Again, the adaptive observation networks were determined using adjoint sensitivities. Third, the optimal observation networks for Asian dust events on the Korean Peninsula were suggested based on the first and second experiments. Section 2 presents the methodology and includes the mathematical formulations, Asian dust cases, and experimental framework. Section 3 describes the results of OSSEs with fixed and adaptive strategies, modified real observation networks, and an optimal observation network. Finally, section 4 presents the summary and conclusions.
2. Methodology

a. Adjoint-based forecast sensitivity

Adjoint sensitivities, which represent the gradient of the response function with respect to the initial condition, have been used to identify sensitive regions for various meteorological features (Kim and Jung 2006; Kim et al. 2008; Jung and Kim 2009; Kim and Kay 2010; Kim et al. 2013). The forecast can be expressed as

\[ x_f = N(x_0), \]  

where \( x_0 \) represents the initial states and \( x_f \) represents the forecast states integrated by the nonlinear model \( N \). The variation of the forecast state \( \delta x_f \) can be expressed as

\[ \Delta x_f \approx \delta x_f = \left. \frac{\partial N}{\partial x} \right|_{x=x_0} \delta x_0 = M \delta x_0, \]  

where \( \delta x_0 \) and \( M(=\partial N/\partial x) \) represent the variation of initial state and tangent linear model, respectively. The response function \( R \) is defined as

\[ R = f(x_f), \]  

where it can be any function of the forecast state that is differentiable.

As mentioned in section 1, meteorological forecast errors affecting Asian dust transport forecasts on the Korean Peninsula are primarily associated with extratropical weather systems and their forecasts (Kim et al. 2013) and flow directions in the lower to midtroposphere (Jhun et al. 1999; Murayama et al. 2001; Kim et al. 2010) over the Korean Peninsula. The location and speed of the high pressure system behind a surface frontal cyclone over the Korean Peninsula affect the flow direction in the lower to midtroposphere over the peninsula, which affects dust forecasts. Therefore, \( R \) in Eq. (3) is defined as the wind forecast error from the surface to midtroposphere (approximately 500 hPa) over the Korean Peninsula (Fig. 1) measured as the kinetic energy at the final time:

\[ R = \iint_{\sigma,\sigma'} \frac{1}{2} (u'^2 + v'^2 + w'^2) \, dx \, dy \, d\sigma, \]  

where \( u', v', \) and \( w' \) are the forecast errors of zonal, meridional, and vertical winds, respectively.

Following Errico (1997) and Kim and Jung (2006), the sensitivity of \( R \) to the initial state can be obtained using the adjoint model \( M^T \) as

\[ \frac{\partial R}{\partial x_0} = M^T \frac{\partial R}{\partial x_f}. \]  

b. Model

For the numerical experiments, the Advanced Research WRF version 3.3 (Skamarock et al. 2008) was used. The model was centered at 45\(^\circ\)N, 115\(^\circ\)E, with a 60-km horizontal grid spacing in 71 (zonal direction) by 55 (meridional direction) horizontal grid points (Fig. 1). The domain had 41 vertical layers, and the top of the model was at 50 hPa. To calculate the adjoint-based forecast sensitivity, the WRFPLUS system (Xiao et al. 2008; Huang et al. 2009), which consists of the adjoint and tangent linear version of the WRF, was used. For the initial and lateral boundary conditions of the model, the National Centers for Environmental Prediction (NCEP) Final Analysis (FNL; 1\(^\circ\) \times 1\(^\circ\) horizontal resolution) and
the Interim European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-Interim; 1.5° × 1.5° horizontal resolution) were used.

c. Cases

Of the 22 Asian dust events that affected the Korean Peninsula from 2005 to 2010, 11 cases with relatively large meteorological forecast errors were chosen for the present study (Table 1) because our aim was to reduce such errors. In Table 1, the origins of dusts were determined using red–green–blue (RGB) imagery of Moderate Resolution Imaging Spectroradiometer (MODIS) data, Multifunctional Transport Satellite-1R (MTSAT-1R) data, the surface and upper-air weather chart, and PM10 concentrations, as in Kim et al. (2013). The occurrence date indicates the day when PM10 concentrations observed on the Korean Peninsula reached the maximum value. The transport time period was determined by the time difference between the maximum PM10 concentrations in the source regions and that on the Korean Peninsula. Only the cases with transport times longer than or equal to 36 h were chosen to evaluate the impact of observation sites upwind of the Korean Peninsula. The final and initial times for model runs were determined according to the time when the PM10 concentrations were at maxima on the Korean Peninsula and 60 h before the final time, respectively.

The average pressure patterns for the 11 Asian dust cases are shown in Fig. 1. At 36 h ahead of the occurrence time of the maximum PM10 concentrations on the Korean Peninsula, the average pressure pattern was characterized by the upper trough extending southward and strong surface pressure gradients west of the surface cyclone over Mongolia and northeastern China (Fig. 1a). The average synoptic pattern during a dust event on the Korean Peninsula was characterized by an upper trough extending southeastward and a well-developed surface cyclone accompanying the eastward movement of the upper trough over the Korean Peninsula at the occurrence time.

In terms of the linearity assumption on which the adjoint sensitivity analysis is based, the ratios of linearly and nonlinearly evolved temperature perturbation magnitudes in the verification area were calculated for each case (not shown). The linearity holds generally well for the 11 cases, which implies that the adjoint sensitivity can be used to identify sensitive regions for meteorological forecasts of the cases.

d. OSSEs

OSSEs were performed for the 11 Asian dust events. The OSSEs require the reference atmospheric state considered to be the “true state,” simulated observations, and a data assimilation system. The data assimilation system used was the WRF three-dimensional variational data assimilation (3DVAR) system (Barker et al. 2004). The background error statistics for this study were generated from 99-day statistics from 2 February to 31 May 2005 using gen_be utilities of
the WRF data assimilation system. The 60-h WRF forecasts using ERA-Interim data as an input were used as the true state (TRUE), and the 60-h WRF forecasts using NCEP FNL data as an input were used as the control state (CNTL) (Fig. 2). In OSSE, the TRUE (i.e., nature run) needs to be within the variability of the real analyses. The mean states of the TRUE are within the variability of the ERA-Interim and the variability of the TRUE is quite consistent with that of the ERA-Interim (Fig. 3). In addition, the position and intensity of the average surface pressure patterns and 500-hPa geopotential height at the initial time of the model integrations and the occurrence times of the maximum PM10 concentration on the Korean Peninsula are quite similar for the TRUE (Fig. 1) and ERA-Interim analysis (not shown), which implies that the TRUE in this study is accurate enough to be regarded as the “truth.” The simulated observations were considered as the upper-air radiosonde observations and obtained by adding observational errors to the TRUE. The simulated wind speed, wind direction, and temperature at 850, 500, and 200 hPa were extracted from the TRUE at the targeting time (0 h), and the observational errors of the radiosonde (Irvine et al. 2011) were added to these wind and temperature variables. New analysis fields were then generated at the targeting time by assimilating the simulated observations to the WRF 3DVAR. The selection criteria dictating where to place the simulated observations are explained in section 3. The EXP runs were obtained by integrating the new analysis for 36 h. The 36-h integration time was chosen because the statistically sensitive regions for the Asian dust events with model integration times greater than 36 h show similar distributions in Kim et al. (2013). The difference between the TRUE and CNTL at the verification time (i.e., final time) was regarded as the forecast error without data assimilation, whereas the difference between TRUE and EXP at the verification time was regarded as the forecast error after assimilating the simulated observations at certain observation sites.

Similar to Eq. (4), the forecast error at specific model layer $\sigma$ over the Korean Peninsula was defined as

$$R(\sigma) = \int \int \frac{1}{2} (u'^2 + v'^2 + w'^2) \, dx \, dy.$$ (6)
The reduction rate of the forecast error at specific model layer was then defined as

$$\text{reduction rate}(\sigma) = \frac{R_{\text{CNTL}}(\sigma) - R_{\text{EXP}}(\sigma)}{R_{\text{CNTL}}(\sigma)} \times 100\%,$$

where $R_{\text{CNTL}}$ and $R_{\text{EXP}}$ indicate the forecast error of the CNTL and EXP run at the verification time, respectively. The vertically averaged reduction rates of the forecast errors were obtained by averaging the reduction rates of the forecast errors at a specific layer for the entire vertical layer. Because the error reduction rates were different for each Asian dust event, the reduction rates of all of the events were averaged to obtain the average reduction rates of the forecast errors.

3. Results

a. OSSE with randomly fixed and adaptive observation networks

1) SELECTION OF OBSERVATION SITES

The fixed observation network was chosen randomly, whereas the adaptive observation network was determined by adjoint sensitivities. To investigate the impact of the number and distance of observation sites on the forecasts, the number of the observation sites was varied among 10, 20, 30, 40, 50, 60, 70, and 80 (Fig. 4), and the distance between observation sites was varied among 120, 180, 240, and 300 km (Fig. 5). The regions in the vicinity (i.e., within 300 km) of the boundaries were excluded when selecting observation sites.
The randomly fixed observation sites for each Asian dust case were selected as follows. The initial 10 fixed observations were chosen randomly (Fig. 4a) and were the same for the 120-, 180-, 240-, and 300-km experiments. An additional 10 observation sites were selected randomly and added to the previous observation network until a maximum of 80 observation sites were established keeping the distance (i.e., 120, 180, 240, and 300 km) between the sites. The simulated observations for each observation network were then produced and assimilated. Each experiment was performed three times with different sets of randomly fixed observation networks to obtain general conclusions. Three different sets of the initial 10 randomly fixed observations are shown in Fig. 6.

To investigate the effect of the adaptive observation network on the forecasts, the sensitive regions for each Asian dust case were identified by adjoint sensitivities and the adaptive observation sites were selected within the sensitive regions as follows. The adjoint sensitivity was calculated for each case, and the time interval between the verification and targeting time was 36 h. One observation site was then determined in the most sensitive region, and the second observation site was selected in the second most sensitive region in consideration of the distance from the first observation site. The subsequent sites were selected in the same way as the previous sites (Figs. 4b and 5b), and then the simulated observations were produced for the selected observation sites and assimilated.

2) CHARACTERISTICS OF FIXED OBSERVATION NETWORK

The OSSEs that used the various observation networks investigated in this study are listed in Table 2. The vertically averaged reduction rates of the forecast errors for FIX_EXP and ADP_EXP that were averaged for all of the Asian dust cases are shown in Fig. 7. The error reduction rates for FIX_EXP were increased as the number of fixed observation sites increased, which implies that assimilating more observations can cover a much larger area in the model domain and resolve more synoptic features to improve the initial condition, as described in Morss et al. (2001). Liu and Rabier (2002) also demonstrated that increasing the density of observations remarkably improved the analysis accuracy in an experimental 1D framework. For the same number of observations, different distances between randomly fixed observation sites can result in a maximum of only 1.4% of the differences in the forecast error reduction rates. For larger numbers (e.g., 60–80) of observation sites, the FIX_EXPs with observation sites that were 240 and 300 km apart reduced the forecast errors more than those with observation sites 120 and 180 km apart. In contrast, for the smaller numbers of observation sites (e.g., 30–40), it is difficult to differentiate the effects at a 240–300-km distance from those at a 120–180-km distance, which implies that larger distances between the fixed observation sites are beneficial for larger numbers of fixed observation sites.
Figure 8 shows the standard deviation of error reduction rates for three different FIX_EXPs using different sets of numbers and distances of randomly fixed observation sites. As the number of observation sites increases, the standard deviations generally tend to decrease. For a small number of observations, it is difficult to resolve the synoptic atmospheric phenomena in the entire domain. Therefore, the error reduction rates vary depending on the specific sets of observation networks with the large standard deviation. In contrast, a large number of observations could resolve the atmospheric phenomena in the entire domain. Therefore, the error reduction rates do not vary widely based on the specific sets of observation networks, although the observation locations are completely different for each observation set. As a result, the standard deviation of the error reduction rates is small. The FIX_EXP with a distance of 120 km generally showed the largest standard deviation (Fig. 8), which implies that the result of the FIX_EXP with 120-km distance varied greatly depending on the specific configurations of the observation locations. This result may have been related to the larger error reduction rates of the 120-km FIX_EXP than those of the 180-km FIX_EXP shown in Fig. 7.

Therefore, a larger number of observation sites can provide more stable forecast error reduction rates. For larger numbers of observation sites, increased distances up to 300 km between the randomly fixed observation sites led to a greater reduction in the forecast error.

3) CHARACTERISTICS OF THE ADAPTIVE OBSERVATION NETWORK

Similar to the FIX_EXP, the average error reduction rates increased in the ADP_EXP as the number of observation sites increased (Fig. 7). However, the forecast error reduction rates of the ADP_EXP oscillated after reaching an almost 10% error reduction, which implies that the 10% error reduction rate may be a saturation rate in the given framework. Bengtsson and Gustavsson (1972) showed that increasing the number of satellite observations beyond a specific value is almost insignificant in an objective analysis and that it is difficult to diminish the RMS error below a certain value. Morss et al. (2001) also showed that adding more observations in the quasigeostrophic (QG) model to the existing dense observations only resulted in a small additional benefit because the analysis errors are small in a dense observation network.

When the distances between observation sites are greater, the forecast errors are reduced more because observations with greater distances can cover most of the sensitive regions. For 10–30 observation sites, the ADP_EXPs with 240- and 300-km distances reduced the forecast errors to a greater extent than those with 120- and 180-km distances. For 40–80 observations, the ADP_EXPs with a 180-km distance reduced the error as much as those with 240- and 300-km distances, whereas the ADP_EXP with a 120-km distance did not reduce the error as much as the other experiments. This finding implies that a 180-km distance EXP is enough to cover the entire sensitive region for the larger number of observation sites but not for the smaller number. In contrast,
the 120-km distance showed the lowest reduction rate among all strategies up to 60 observation sites and yielded similar results to the other distances for 70–80 observation sites, which indicates that the ADP_EXP with the 120-km distance cannot cover the domain using the smaller number of observation sites. Similar to the FIX_EXP, increased distances between the adaptively selected observation sites reduced the forecast errors to a greater extent for the larger numbers of observation sites.

For both FIX_EXP and ADP_EXP, the average error reduction rates generally increase as the numbers of observation sites increase and the distance between the observation sites becomes greater up to 300 km. Overall, the ADP_EXP shows a greater error reduction rate than the FIX_EXP, excluding the ADP_EXP with a 120-km distance. The smaller error reduction rates of the ADP_EXP compared to the FIX_EXP for the 120-km distance were caused by observation sites that were too closely clustered in the sensitive regions (Fig. 5b). The discrepancies between the ADP_EXPs with various distances are generally larger than those between the FIX_EXPs (Fig. 7) because the observation locations of the ADP_EXPs vary greatly compared to those of the FIX_EXPs depending on the distances between the observation sites (cf. Figs. 5a and 5b). However, excluding the 120-km distance, the discrepancies between the ADP_EXPs decrease considerably and become similar to those between the FIX_EXPs as the number of observation sites increases, which implies that the ADP_EXPs with the distance from 180 to 300 km result in similar error reduction rates for the larger number of observation sites. The FIX_EXP can reduce the forecast error by more than 8% for more than 70 observation sites, whereas the ADP_EXP can reduce the forecast error to the same extent for more than 40 observation sites, excluding the 120-km experiments. Therefore, compared to the randomly fixed observation network, the adaptive observation network is more efficient at reducing the forecast error with lower numbers of observation sites if the observation sites are adequately separated.

The OSSEs (i.e., FIX_EXPs and ADP_EXPs) with the cycling data assimilation (−6 and 0 h) and with simulated observations extracted from six layers (850, 700, 500, 300, and 200 hPa) were also tested to evaluate the effect of the cycling and doubling the vertical layers on the OSSE results. The cycling data assimilation and doubling the vertical layers to extract the simulated observations did not affect major features of the results (not shown).

b. OSSE with a modified real observation network

1) REDISTRIBUTION AND ADDITION STRATEGY

Because the 77 real upper-air observation sites were already established in East Asia, experiments with the real observation network in the model domain (Fig. 9) were performed to suggest the observation network that is optimal to decrease the meteorological forecast error. In the real observation network, the distances between radiosonde observation sites are generally from 200 to 400 km. The OSSEs in Table 2 were applied to the 11 Asian dust cases, and the mean reduction rates of the forecast errors were obtained by averaging the error reduction rates for each case.

The RDS_ADP_EXP was implemented as follows. First, the distances from each observation site to the other observation sites were calculated and ordered by distance. The two observation sites with the shortest distance to each other were selected among all of the real observation sites. The observation site with the shorter distance to the next closest observation site was selected from the two observation sites and removed. Second, the observation site in the most sensitive grid point was selected. If the distances between the selected observation

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**Table 2. The observing system simulation experiments using various observation networks.**

<table>
<thead>
<tr>
<th>Type of observation network</th>
<th>Expt name</th>
<th>Characteristics of expt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed and adaptive</td>
<td>FIX_EXP</td>
<td>OSSE using the randomly selected fixed observation sites</td>
</tr>
<tr>
<td>observation network</td>
<td>ADP_EXP</td>
<td>OSSE using the observation sites determined by the adaptive strategy</td>
</tr>
<tr>
<td>Modified real observation</td>
<td>RDS_FIX_EXP</td>
<td>OSSE using the real observation sites partly redistributed by the randomly fixed strategy</td>
</tr>
<tr>
<td>network by redistribution</td>
<td>RDS_ADP_EXP</td>
<td>OSSE using the real observation sites partly redistributed by the adaptive strategy</td>
</tr>
<tr>
<td>Modified real observation</td>
<td>ADD_FIX_EXP</td>
<td>OSSE using the real observation sites, added new observation sites by the randomly fixed strategy</td>
</tr>
<tr>
<td>network by addition</td>
<td>ADD_ADP_EXP</td>
<td>OSSE using the real observation sites, added new observation sites by the adaptive strategy</td>
</tr>
</tbody>
</table>
site and the existing observation sites (i.e., real or adaptive observation sites) were more than 180 km, then the selected observation site replaced the real observation site that was removed; if not, then the observation sites in the second most sensitive grid point were selected and replaced the real observation site that was removed. Third, observations at the new observation network were assimilated. The RDS_ADP_EXP was conducted by varying the number of redistributed observation sites from 1 to 17 (approximately 22% of the total 77 sites) by increments of 1. When the number of redistributed sites increased, the distances between the real observation sites were recalculated and the entire process was repeated. Figure 9a is an example of a new observation network containing 17 redistributed observation sites. RDS_FIX_EXP was the same as RDS_ADP_EXP except that the removed real observation sites were replaced by the randomly chosen fixed observation sites.

For ADD_ADP_EXP, the adaptive observation sites determined by adjoint sensitivities were added to the real observation network. Experiments were conducted by varying the number of newly added observation sites from 1 to 13 by increments of 1 in consideration of the 180-km distance among the added adaptive observation sites and existing observation sites. The selection of the added observation sites in the sensitive regions was the same as in RDS_ADP_EXP. Figure 9b is an example of a newly organized real observation network in which 13 observation sites were added adaptively. ADD_FIX_EXP was the same as ADD_ADP_EXP except that the newly added observation sites were selected randomly.

2) CHARACTERISTICS OF THE REDISTRIBUTED OBSERVATION NETWORK

Figure 10a shows the mean error reduction rates of RDS_ADP_EXP and RDS_FIX_EXP. The forecast error was reduced by 8.9%, on average, when the observations were assimilated on the real observation sites without redistribution (black bar in Fig. 10a). Except for the experiment with one redistributed observation site, RDS_ADP_EXP showed greater mean error reduction rates than RDS_FIX_EXP (Fig. 10a), which implies that adaptive redistribution is a better strategy for improving forecast performance than random redistribution for the observation sites 180 km apart when more than one observation site are redistributed. In addition, compared to the error reduction rate of the real observation network (black bar), adaptive redistribution of less than five observation sites of the real observation network degrades the forecast performance. Therefore, the accuracy of the forecasts in redistributed real observation networks was improved when more than a certain number of observation sites were adaptively redistributed, which implies that the number of redistributed observation sites...
observations should be large enough to cover entire sensitive regions. The linear regression result between the number of adaptively redistributed observation sites and forecast error reduction rates is shown in Fig. 10a. An increasing trend of mean error reduction rates with more adaptively redistributed observation sites is shown in Fig. 10a.

3) CHARACTERISTICS OF THE ADDED OBSERVATION NETWORK

Figure 10b shows the mean forecast error reduction rate for the newly organized real observation network, which consists of real observation sites and added adaptive observation sites. Adding adaptive observation sites to the real observation network always improves the forecast and reduces the forecast error by more than 8.9%. Generally, the error reduction rate of the adaptive addition strategy is always greater than 10% for more than four observation sites added. ADD_FIX_EXP can reduce much smaller forecast errors than ADD_ADP_EXP, even if ADD_FIX_EXP improves forecast performance (Fig. 10b), which indicates that the forecast improvement is caused not just by adding more observation sites and covering larger regions but by adding observation sites and covering sensitive regions. Thus, it can be concluded that assimilating observations in sensitive regions determined by large adjoint sensitivities have a notable impact on forecast performance and that adding adaptive observation sites can effectively improve forecasts.

It is important to compare the redistribution strategy with the addition strategy to determine which one is more effective at modifying the real upper-air observation network. As shown in Figs. 10a and 10b, adding adaptive observation sites improves the forecast performance compared to the redistribution of observation sites. For the 180-km distance, irregular numbers (e.g., 9, 14, 15, and 17) of the 77 real observation sites must be redistributed to obtain a forecast error reduction rate greater than 10% (Fig. 10a), whereas adding more than four adaptive observation sites can reduce the same amount of the forecast error (Fig. 10b). Because the total number of observation sites in the addition strategy is greater than that in the redistribution strategy, the forecast error reduction rate of the addition strategy could be greater than that of the redistribution strategy. To enable a fair comparison, the error reduction rate per observation site was obtained by dividing the error reduction rate by the total number of observation sites. The error reduction rate per observation site was almost same as that in Fig. 10 (not shown).

The impact of adding a small number of observation sites was similar to that of redistributing a large number of observation sites. Therefore, the addition strategy is a more efficient method of reducing forecast error than the redistribution strategy. Furthermore, adding adaptive observation sites improves the forecast performance to a greater extent than adding random observation sites. Thus, the forecast improvement is not caused by increased observations but by observations assimilated in sensitive regions.
c. OSSE with an optimal meteorological observation network

1) STATISTICALLY SENSITIVE REGIONS

Until now, each sensitive region for each Asian dust event had been used to implement the experiments, and the results were averaged statistically. In reality, however, it is unfeasible to detect each sensitive region and assimilate the adaptively selected observations for each case. Thus, it is crucial to determine the statistically sensitive regions for the 11 Asian dust events and verify whether the observation sites in the sensitive regions have positive effects on the meteorological forecast performance of Asian dust events. To obtain statistically sensitive regions, sensitive grids that include the most sensitive upper 5% of all grids in the domain were selected for each case using adjoint sensitivities. These grids were considered to have one frequency, and the frequencies were then integrated for all 11 cases.

Figure 11 shows the statistically sensitive regions with an average 500-hPa geopotential height at the targeting time for the 11 Asian dust cases. Two sensitive regions were identified: the maximum sensitivity was located in the Gobi, and the next maximum sensitivities were located in northeastern China (Manchuria), the Liaodong Peninsula, and North Korea. These sensitive regions coincide with the northern dust source regions that are identified as statistically sensitive regions for 46 Asian dust events affecting the Korean Peninsula from 2005 to 2010 in Kim et al. (2013). The mean pressure trough in the upper air was located over sensitive regions in the Gobi. The sensitive regions were located under the upper trough in the strong pressure gradient regions behind the frontal cyclone (cf. Fig. 1a). The locations of the upper trough and surface cyclone were associated with the statistically sensitive regions before and during the Asian dust event on the Korean Peninsula (Kim et al. 2013).

2) CHARACTERISTICS OF THE OPTIMAL METEOROLOGICAL OBSERVATION NETWORK

It is important to verify whether these statistically sensitive regions have a significant impact on the meteorological forecast performance of individual Asian dust events. Based on the procedures described in section 3b, the adaptive addition strategy was selected to organize the new observation network. Similar to the previous experiments, additional observation sites were selected in statistically sensitive regions and added to the real observation network in consideration of the 180-km distance between the new observation sites and the existing observation sites. The number of additional observation sites was then increased from 1 to 13. Figure 11 shows the newly organized optimal observation network with 13 added observation sites superimposed on statistically sensitive regions and 500-hPa geopotential height. The mean error reduction rates for the newly organized observation network are shown in Fig. 12a. Regardless of the number of observation sites added, the average performance of the forecast was improved. The mean error reduction rate was 10%, with a maximum of 10.6% when eight observation sites were added. When more than eight observation sites were added, the error reduction rates fluctuated around 10%, which was the saturation point in this framework.

Because the statistically sensitive regions were indirectly associated with each case, cross-validation-type experiments were also performed to obtain a more general result (Fig. 12b). The 11 cases were divided into two groups: one group for prescribing the statistically
sensitive regions and the other for the impact experiments. For more than nine observation sites added, the average of several different configurations of the cross-validation experiments show more error reduction than the original experiment shown in Fig. 12a, which may be due to the averaging effect of the several cross-validation experiments. However, the characteristics of the mean error reduction rates were generally similar for the original experiment (Fig. 12a) and the average of the cross-validation experiments (Fig. 12b), which reaffirms that the statistically sensitive regions and adaptive addition strategy have a significant impact on the meteorological forecast of Asian dust events.

Forecasting was improved when statistically sensitive regions were considered for each case, although the statistically sensitive regions were not directly associated
with each case. The mean error reduction rate when considering sensitive regions for each case (Fig. 10b) was 10.4%, with a maximum of 11.2%, whereas for the statistically sensitive regions (Fig. 12a), the mean error reduction was 10%, with a maximum of 10.6%. Better forecast performance shown in Fig. 10b is expected because each sensitive region was considered for each case. This finding indicated that adding observation sites in specific sensitive regions of each case was more efficient than adding observation sites in statistically sensitive regions because the statistically sensitive regions may not be relevant to specific sensitive regions associated with each case. Overall, the mean error reduction rate of the addition strategy in the statistically sensitive regions was greater than that of the random addition strategy and less than that of the adaptive addition strategies for individual cases (cf. Figs. 10b and 12a). For both ADD_ADP.EXP and the addition experiment in the statistically sensitive regions, the mean error reduction appeared to be saturated when the number of observation sites approached 8 or 9 (Figs. 10b and 12a) even though this feature may be relaxed when performing the cross-validation experiments using more cases. Nevertheless, adding observation sites in statistically sensitive regions improved meteorological forecast performance. Therefore, statistically sensitive regions can provide useful guidance for establishing new observation sites or for using available observations (e.g., satellite observations) to more accurately detect meteorological states.

4. Summary and conclusions

Because Asian dust phenomena occur upwind of the Korean Peninsula and move eastward and meteorological forecasting is crucial for the accurate prediction of Asian dust transport events to the peninsula, the observation network upwind of the Korean Peninsula should be designed appropriately to represent the flow fields. The observations obtained from the observation network can be assimilated to produce more reliable initial meteorological conditions.

To investigate the effect of observation network design on the meteorological forecasts during Asian dust events on the Korean Peninsula, 11 dust events affecting South Korea in a recent 6-yr period were selected and a series of observation system simulation experiments were conducted using the WRF modeling system, which includes the WRF adjoint model and 3DVAR. The impact of the distribution of observation sites on the forecast performance was investigated by assimilating the simulated observations from randomly fixed and adaptively selected observation sites. The adaptive observation strategy was able to reduce the forecast error more efficiently than the fixed observation strategy. For the adaptive observation strategy, as the distance between observation sites became greater up to 300 km, the reduction of forecast errors increased, on average, in the current framework. As the number of observation sites increased, the reduction of the forecast error increased for both randomly fixed and adaptive strategies. However, for the adaptive observation network, as the reduction rate of forecast error reached the saturation point (10%), the forecast error was no longer reduced but instead fluctuated even though more observation sites were used.

To incorporate an adaptive observation network into the real observation network, the effects of redistributing the real observation network and adding adaptive observation sites were investigated. The real upper-air observation network consists of 77 radiosonde sites in the model domain, which include the Korean Peninsula, China, Mongolia, and Russia. Adding adaptive observation sites to the real observation network produced a greater improvement for the forecast performance than did redistributing the existing observation sites. Because it is not feasible to use each sensitive region for each case to design an optimal observation network, statistically sensitive regions for 11 Asian dust events were used. The sensitive regions appeared near the upper trough and the accompanying surface cyclone, which are related to Asian dust events. When additional observations were added to statistically sensitive regions over the real observation network, the forecast accuracy
was improved, although the performance resulting from adding adaptive observation sites in the statistically sensitive regions was slightly less than that in sensitive regions of individual cases. Therefore, adding observations in statistically sensitive regions should have a beneficial impact on the meteorological forecast performance of Asian dust events. Furthermore, statistically sensitive regions could provide useful guidance for the effective placement observation sites to detect meteorological conditions accurately.

As mentioned in the introduction, to accurately predict Asian dust, it is crucial to improve the quality of the initial conditions of both the meteorological fields and the dust emissions because dust transport models require this information as input. Therefore, future work would include using a response function that incorporates the errors in dust emission and further using the adjoint sensitivity distributions for both meteorological and dust emission processes of Asian dust events, which would provide more comprehensive conclusions regarding the optimal
observation network of Asian dust forecasts. In addition, using other adaptive strategies that can calculate the sensitive regions by considering the effect of redistributing and adding observation sites would further help with understanding the effect of the observation network on the meteorological forecasts of Asian dust events.

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