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Atmospheric Chemistry and Physics Discussions

A data assimilation method of the Ensemble Kalman Filter for use in severe dust storm forecasts over China

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Abstract

An Ensemble Kalman Filter (EnKF) data assimilation system was developed for a regional dust transport model. This paper applied the EnKF method to investigate modeling severe dust storm episodes occurred in March 2002 over China based on surface observations of dust concentrations to explore its impacts on forecast improvement. A series of sensitivity experiments using our system reveals that the EnKF is an advanced assimilation method to afford better initial conditions with surface observed PM_{10} in North China and lead to improved forecasts of dust storms, but forecast with large errors can be made by model errors. This result illustrates that it requires identifying and correcting model errors during the assimilation procedure in order to significantly improve forecasts. Results also show that the EnKF should use a large inflation parameter to obtain better model performance and forecast potential. Furthermore, the ensemble perturbations generated at the initial time should include enough ensemble spreads to represent the background error after several assimilation cycles.

1 Introduction

Dust storms have drawn much concern during the past two decades for its various impacts on atmospheric environment, biogeochemical cycles, radiative balance and human health. In recent years, many observations have been carried out to study Asian dust storms and much progress has been achieved and improved the understanding of climatic and synoptic features of soil dust aerosols (Murayama et al., 2001; Mori et al., 2002; Sugimoto, 2002; Sugimoto et al., 2002; Zhang et al., 2003). On the other side, for the special ability to provide high spatial and temporal resolution forecasts of Asian dust and reproduce many important observational facts, several numerical models have been developed and used to study the deflation, transport and budget of soil dust over East Asia (Wang et al., 2000; Shao, 2001; Song et al., 2001; Uno et al., 2001; Gong et al., 2003; Shao et al., 2003; Park et al., 2003; Liu et al., 2003; Han et al., 2004). The intercomparison study (DMIP) involving eight dust emission/transport models over Asia found that the model results correctly captured the major dust onset and cessation timing at each observation site. However, the maximum concentration of each model was 2–4 times different (Uno et al., 2006), clearly indicating that modeling results of dust storms with these models have significant errors.

Numerical forecasts of dust storms suffer from uncertainties of initial conditions, emission and model errors. Simply comparing model forecast to observations can not separate these uncertainties. Using data assimilation technique we can firstly reduce uncertainty of initial conditions that may lead to improved forecasts and secondly better examine model errors by comparing to observations since the uncertainty of initial conditions can be maximally reduced by assimilation of observations at initial times. Recently, Yumimoto et al. (2007) applied a four-dimensional variation (4-DVAR) to a regional dust model to assimilate NIES Lidar observations over East Asia to inverse Asian dust emissions and shown better estimation capability. Niu et al. (2007) developed a 3-DVAR using satellite retrieved dust loading and surface visibility in CUACE/Dust forecast system and showed the capability of short-term forecast improvement. These both indicate the important role of data assimilation to combine the observations and model in dust forecast. In these methods, the background error statistics, one of the most important items in data assimilation, are usually assumed to be spatially homogeneous, horizontally isotropic, and temporally stationary, which may disagree with the true ones that may have significant flow-dependence, especially for meso-scale motions. Although the background error statistics can evolve implicitly in 4-DVAR during the time window, the complexity of constructing the adjoint matrix and the expensive computation in 4-DVAR usually prevent it from common application especially for complicated models.

In this study we perform Ensemble Kalman Filter (EnKF) data assimilation experiments during some severe dust storm episodes in China using surface observations of dust concentrations and a realistic model in order to explore the impacts on forecast improvement. The EnKF is an advanced, flexible and widely used technique for data assimilation which can calculate the flow-dependent statistics from the ensemble forecasts (Evensen, 1994; Houtekamer and Mitchell, 1998, 2001; Mitchell and Houtekamer, 2000, 2002; Houtekamer et al., 2005; Whitaker et al., 2002; Lorenc, 2003; Evensen, 2003, 2006). However EnKF has not been applied in severe dust storm forecasts, for the first time, we made an initial effort to explore the potential problems of this issue with EnKF.

2 Data source and model description analysis

2.1 Data

Daily averaged PM_{10} concentrations observed by the State Environmental Protection Administration, China (SEPA) from 15 March 2002 to 25 March 2002 are used for assimilation and validation. For the PM_{10} observations reflect not only dust aerosol but also anthropogenic aerosol, before they are used, the PM_{10} observations are selected according to the surface synoptic observations about dust events every 3 h from China Meteorological administration (CMA). If there are at least one occurrence of floating dust phenomenon observed at stations located within 1 latitude degree around the PM_{10} station during the day, the contribution of PM_{10} observation of this station of the day is considered mainly coming from dust and selected for assimilation and validation, otherwise it would be discarded. The number of qualified PM_{10} observations after quality control is listed in Table 1, clearly indicating the influence of dust storms on the air quality. Figure 1 presents the distribution of observation sites (green dots) passing through quality control and used for assimilation on 22 March, and the red rectangles represent three selected independent sites that only used for verification.

The Lidar observation at Beijing was performed at the Sino-Japan Friendship Center for Environmental Protection during the same period (Sugimoto et al., 2003). The visibility observations are the surface observations from the China Metrological Administration (CMA).

2.2 Model description and setting

The regional dust transport model (Wang et al., 2000) included deflation, transport, diffusion, and removal processes during the life cycle of the yellow sand particles. This model had been successfully used to study atmospheric trace gases and particles, such as SO_x, dust, O_3 and acid rain over East Asia (Wang et al., 2000, 2002; Uematsu et al., 2003). The advanced deflation module of yellow sand has been designed after detailed analysis of the meteorological conditions, landform, and climatology from daily weather report at about 300 local weather stations in north China. Details about the model could be referred to Wang et al. (2000). The simulation domain used ranges from (75° E, 16° N) to (146° E, 60° N) consisting of 72 by 45 grid cells horizontally and 18 vertical layers is shown in Fig. 1.

A heavy dust storm occurred in northern China and invaded Beijing on 20 March 2002, with peak concentration of Total Suspended Particles (TSP) reaching 10.9 $\mathrm{mg\,m^{-3}}$, 54 times higher than the National Air Quality Standard of China (Sun et al., 2004). Model analysis with Lidar observation of this dust storm in Beijing revealed the source and transport path of the dust and further explained the reasons for the occurrence of such extremely high dust concentration (Sugimoto et al., 2003). This dust storm not only swept over most parts of China but also reached Korea and Japan. Using model simulation, Park et al. (2003) studied dust emissions from the source areas of this dust storm. In addition, Shao et al. (2003) simulated this dust storm with an integrated modeling system and found the model could predict well the spatial pattern and temporal evolution of dust concentration. Han et al. (2004) developed a size-segregated aerosol model and coupled this with a regional air quality model to simulate the dust storms of 15–24 March 2002. In this study, we developed a regional chemical transport model combined with EnKF data assimilation method to improve the forecast performance and to investigate the vertical structure of this super dust storm during the period of 15–25 March 2002 in East Asia.

3 Data assimilation with Ensemble Kalman Filter method

The basic idea of the EnKF (Evensen, 1994) is to construct a Monte Carlo ensemble such that the mean of the ensemble is the best estimate, and the ensemble error covariance is a good estimate of the forecast error covariance.

At the current assimilation time, the EnKF assumes that the forecast error is randomly sampled by an ensemble of forecasts, denoted by $\mathbf{x}_1^b, \mathbf{x}_x^b, \cdots, \mathbf{x}_m^b$. The ensemble mean is defined by $\overline{\mathbf{x}}^b = m^{-1} \sum_{i=1}^{m} \mathbf{x}_i^b$. The ensemble perturbation from the mean for i-th member is $\mathbf{x}'_{ib} = \mathbf{x}_i^b - \overline{\mathbf{x}}^b$. The EnKF performs an ensemble of parallel assimilation circles, $i=1, \ldots,$ m, with each member update to different realization of the observations:

$$\mathbf{x}_i^a = \mathbf{x}_i^b + \hat{\mathbf{K}}(\boldsymbol{y}_i - H(\mathbf{x}_i^b)). \tag{1}$$

In Eq. (1), $\mathbf{y}_i \approx N(0, \mathbf{R})$ is a perturbation from observations y. And the gain matrix $\hat{\mathbf{K}}$ can be formed without ever explicitly computing the full forecast error covariance (Evensen, 1994; Houtekamer and Mitchell, 1998) using the following equations:

$$\hat{\mathbf{K}} = \hat{\mathbf{P}}^b H^T (H \hat{\mathbf{P}}^b H^T + \mathbf{R})^{-1}, \tag{2}$$

$$\hat{\mathbf{P}}^b H^T = \frac{1}{m-1} \sum_{i=1}^{m} \mathbf{x}'_{ib} (H(\mathbf{x}_i^b) - \overline{H(\mathbf{x}^b)})^T, \tag{3}$$

$$H \hat{\mathbf{P}}^b H^T = \frac{1}{m-1} \sum_{i=1}^{m} (H(\mathbf{x}_i^b) - \overline{H(\mathbf{x}^b)})(H(\mathbf{x}_i^b) - \overline{H(\mathbf{x}^b)})^T. \tag{4}$$

In Eq. (3) and Eq. (4),

$$\overline{H(\mathbf{x}^b)} = \frac{1}{m} \sum_{i=1}^{m} H(\mathbf{x}_i^b).$$

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Once each member is updated, we take the mean $\overline{\mathbf{x}}^a = m^{-1} \sum_{i=1}^{m} \mathbf{x}_i^a$ as the analysis.

In this study, the initial background ensemble perturbations are generated by adding random amplitude and phase shifts to the first-guess $\mathbf{x}(x, y, z)$ as follows:

$$\mathbf{x}_i(x, y, z) = (1 + \delta_i)\,\mathbf{x}\,(x + \varepsilon_i, y + \omega_i, z + \eta_i)$$

where,

$$\delta \in N(0, a^2), \varepsilon \in N(0, l_x^2), \omega \in N(0, l_y^2), \eta \in N(0, l_z^2),$$

and the observations are also perturbed with a normal distributed noise with zero mean and variance **R**.

A parameter $\alpha \geq 1$ is introduced to allow for inflating the forecast error variance since the ensemble spread itself may be too small to draw the model states to the observations, then Eq. (2) will be rewritten as

$$\hat{\mathbf{K}} = \alpha \hat{\mathbf{P}}^b H^T (\alpha H \hat{\mathbf{P}}^b H^T + \mathbf{R})^{-1}. \tag{5}$$

In addition, the value for dust concentrations should be positive that the analysis would be set to be zero if it is negative.

4 Results

Two sets of run with and without assimilation scheme addressed above were performed to test the performance of the EnKF used in the regional transport model of dust. Firstly, the tests were performed during 15–25 March 2002 once a day with initial perturbations generated on 03:00 UTC 15 March to check the overall impact of the assimilation on 24 h forecasts.

To convey an impression of the anisotropic nature of the horizontal correlations, we present some examples of horizontal correlations of surface concentrations with respect to the points shown with the black dots in Fig. 2 and Fig. 3. The correlations are

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directly estimated from 50-member ensemble on 03:00 UTC 16 March and 20 March. It can be seen that the spatial structure are dependent on the flow which displays the most important property of EnKF compared to other traditional data assimilation methods such as optimal interpolation (OI) and three-dimension variational assimilation (3-D-Var). In OI and 3-D-Var algorithms, the statistics in background error covariance are generally taken to be isotropic and largely homogeneous with little variation in time which is not consistent with the real systems.

The root mean square (RMS) difference between daily averaged PM_{10} observations and the simulated daily averaged 24 h forecasts (d<10 μm) and the analysis at three independent observation stations were calculated during 16–25 March 2002 (Fig. 4). It can be seen that the RMS difference of the assimilated results are much smaller than that without assimilation totally, which clearly shows the potential ability of the EnKF method used in the regional transport model. The RMS difference for all sites is shown in Fig. 5. The difference between observations and the 24 h forecasts with assimilation are smaller than those without assimilation, showing the forecast are also improved after EnKF assimilation but not obviously for the whole area.

An independent Lidar observed the dust extinction coefficients in Beijing in the same period. Figure 6 gives comparison between Lidar observations, model simulation without assimilation and assimilated dust concentrations. These results illustrated that to use the EnKF method only assimilating surface PM_{10} concentration changed the vertical structures of dust distribution and significantly improved the modeling results in Beijing when comparing with Lidar observations. Two peaks of dust concentration distribution exhibited on 20 March in Beijing with EnKF assimilation agrees well with the dust extinction coefficients. This may be due largely to the vertical structure in background error covariance calculated from the ensemble, which propagates the surface PM_{10} observations to high levels.

Surface dust concentrations and visibility are compared in Beijing in Fig. 7. On 20 March, the two troughs of visibility correspond to the two peaks of dust concentrations with assimilation but just one peak of the simulated results without assimilation, and the bigger trough corresponding to the higher peak. This makes clear that the Ensemble Kalman Filter plays an important role on it. Figure 8 shows the assimilated results of surface dust aerosols (d<10 μm) with assimilation once a day at three independent observed stations respectively (A, B, C as shown in Fig. 1). It shows that the assimilation analyses are closer to the observations than the simulation without EnKF assimilation especially in Shijiazhuang (B) and Shanghai (C). The assimilated results in Dalian (A) are not so closer to the observations as the simulation, which may be due to the sparse observations nearby and the low resolution of model. If the observational network is relatively dense the assimilated results are better, such as the results of B and C.

We here select point A (Dalian) to explain it. For Dalian, the analyses on 17 March and 21 March are worse than simulation, the others are comparable to the simulation. From Fig. 9 we can see that the variation of observed PM_{10} of two close points (Dalian and Qinhuangdao) are quite different, especially on 17 March and 21 March, which indicates that spatial variability of the dust storm is very strong and the correlation coefficient is small in fact. However, the resolution of model is $1^{\circ}\times 1^{\circ}$, which may be too low to resolve the spatial variability of such processes, and then the dust concentrations calculated from the model are similarly distributed in a relatively large region. So the correlations estimated directly from the ensemble forecasts are distributed in a relative large region, which does not agree with the real one and it can bias the assimilated results. Figure 10 gives the correlation distribution of Dalian on 17 March (upper panel) and 21 March (bottom panel), and the black dot and the green dot denote the position of Dalian and Qinghuangdao respectively. We can see that the correlation coefficients of these two points are larger than 0.8. Therefore, the method to solve it is to increase the model resolution or to try to get much denser observations.

Figure 11 and Fig. 12 give surface distribution of dust concentration over East Asia without (a) and with assimilation (b) on 20 and 21 March, respectively. Compared with the PM_{10} observations, the forecast concentrations are much larger than the observations, especially in the north part of North China, while smaller in the south part. After EnKF assimilation, the average of one-day forecast concentrations decreases in the north part and increases in the south part of North China, which compensates the model deficiency.

5 Conclusion and discussion

The correlation patterns of several selected points shown in Fig. 2 and Fig. 3 prove that EnKF can calculate the flow-dependent statistics which may not be expected in other traditional assimilation techniques. To use surface PM_{10} observations for data assimilation of dust storm, it is necessary to select them according to the surface synoptic dust events reports. This study shows that, using advanced method such as EnKF, the assimilation of surface PM_{10} observations can provide better initial conditions and lead to improved forecasts of dust storms. However the forecasts still have large space to be further improved. First, the current PM_{10} observations that are reported to in SEPA are only daily-averaged. For fast changing processes such as dust storms, this study shows that much more frequent observations are needed to correctly describe the fast evolution structure. And denser observational networks are also necessary to specify the spatial variability of such process as air pollution (see Fig. 8). Second, the model errors are main contributions to forecast errors at least at some regions. The assimilation can provide good initial conditions, but forecast with large errors can be made by model errors (see Fig. 5). Therefore it requires identifying and correcting model errors during the assimilation procedure in order to significantly improve forecasts. This may be achieved by either four-dimensional variation method or augmented EnKF. This should be a priority for further studies in this direction.

The dust concentrations vary very rapidly and are generally independent in different dust process. Therefore, the ensemble perturbations generated at the initial time may not have enough ensemble spread to represent the background error after several assimilation cycles. In this study we found it is necessary to use a large inflation parameter (α defined in Eq. 5). In addition, we also found that the analysis may have negative values for dust concentrations. We use a simple way that sets negative values to zero. More skillful methods should be explored in further studies.

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Table 1. Number of valid PM10 observations after quality control over North China during 15–25 March 2002.

Date	15	16	17	18	19	20	21	22	23	24	25
No. of Obs.	0	6	16	10	11	12	17	23	8	4	0

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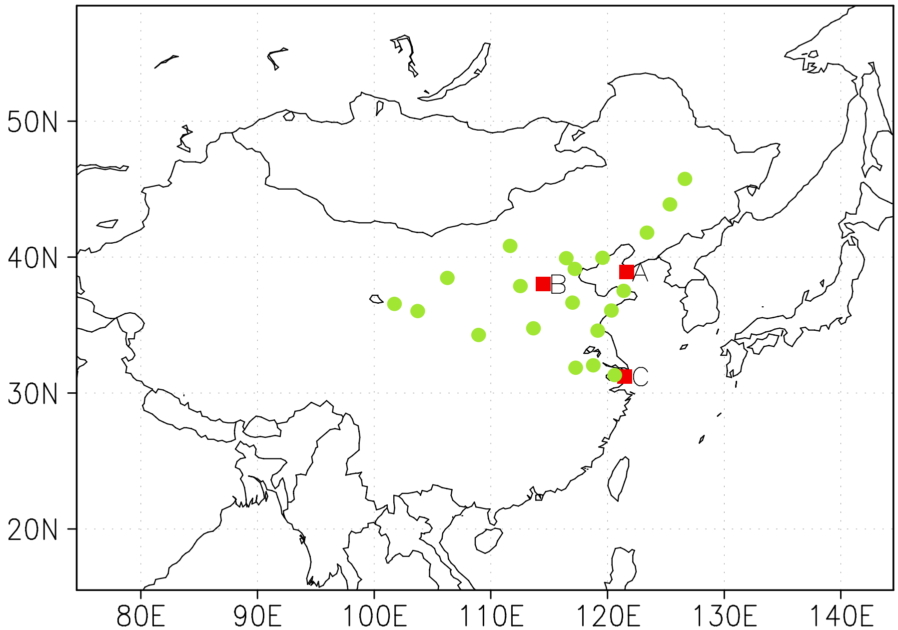

Fig. 1. The model domain and the observational network . The closed circles indicate positions of those PM_{10} observations used in assimilation cycles on 22 March, while the rectangles are those used for independent verifications.

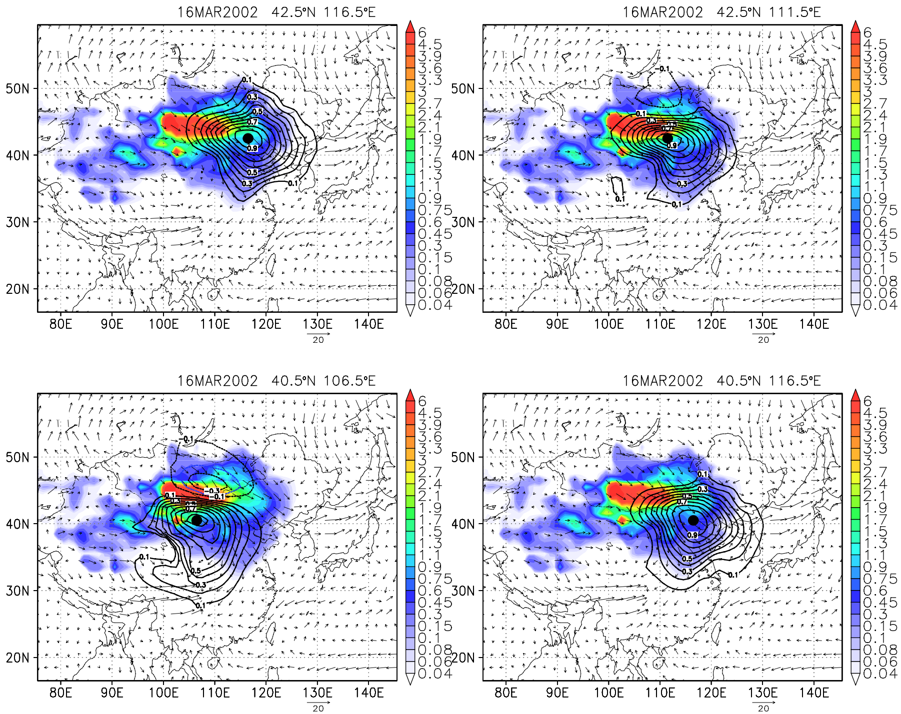

Fig. 2. Correlations (line contours) of surface concentrations with those at different points denoted by the black dots directly estimated from ensemble perturbations at 03:00 UTC on 16 March 2002. The shaded contour is the simulated surface concentrations of dust particles.

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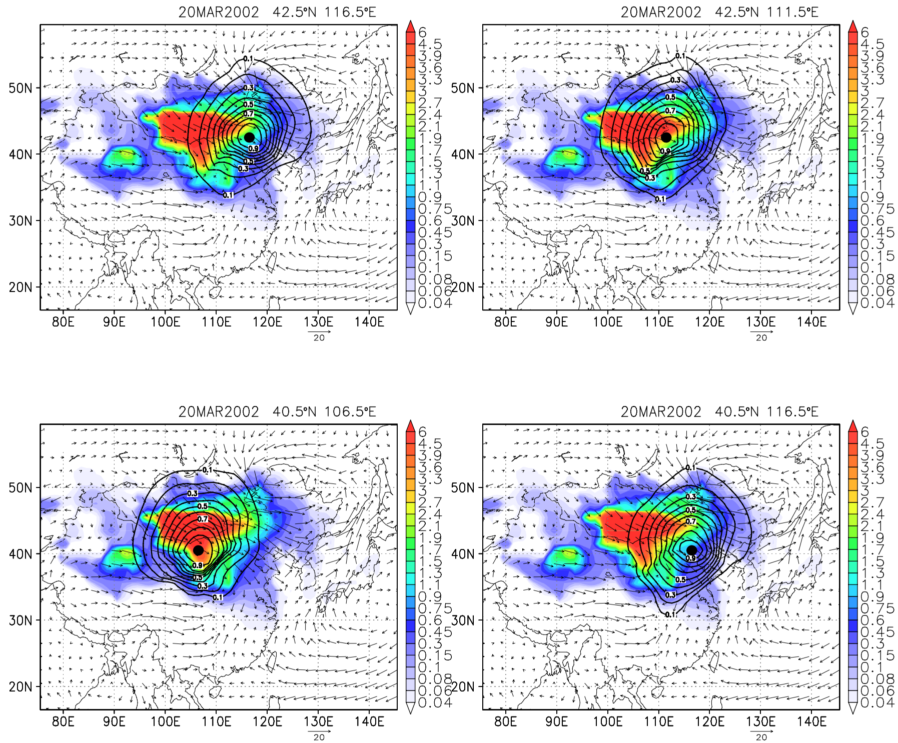

Fig. 3. As in Fig. 2, but at 03:00 UTC on 20 March 2002.

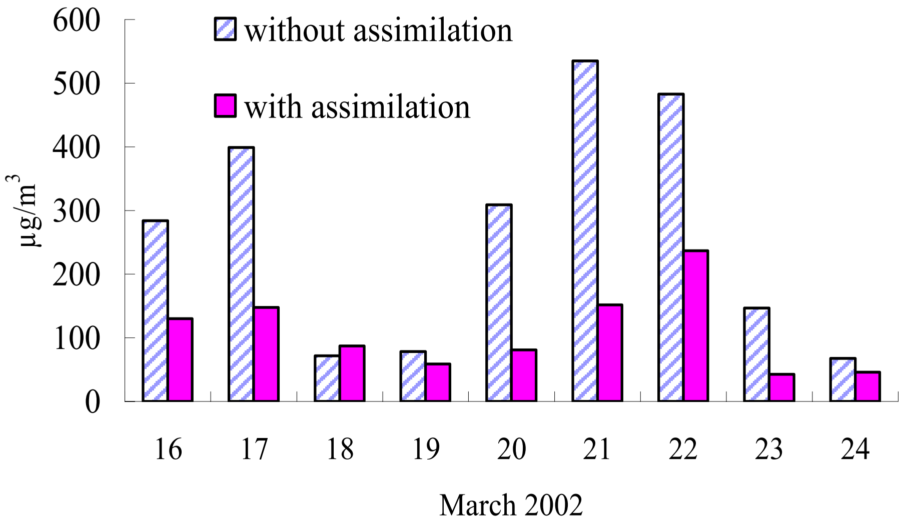

Fig. 4. Comparison of RMS (the root mean square) error between observed daily-mean PM_{10} levels and predicted dust aerosols concentrations (d<10 μm) at three independent validation sites without assimilation (line rectangle) and with EnKF assimilation analysis (shaded rectangle) during 16–24 March 2002 when there are observations at three independent verification sites passing through quality control. The 10-day assimilation cycle is used for EnKF analysis.

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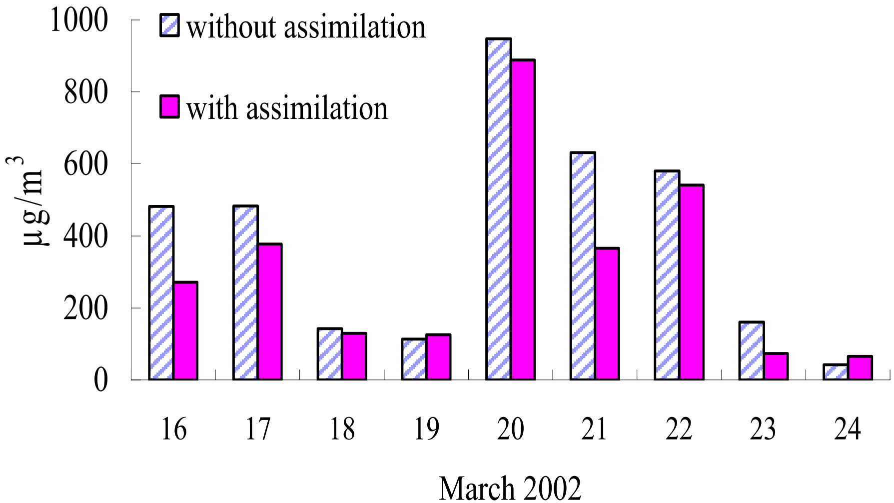

Fig. 5. Same as Fig. 4, but for all observational sites.

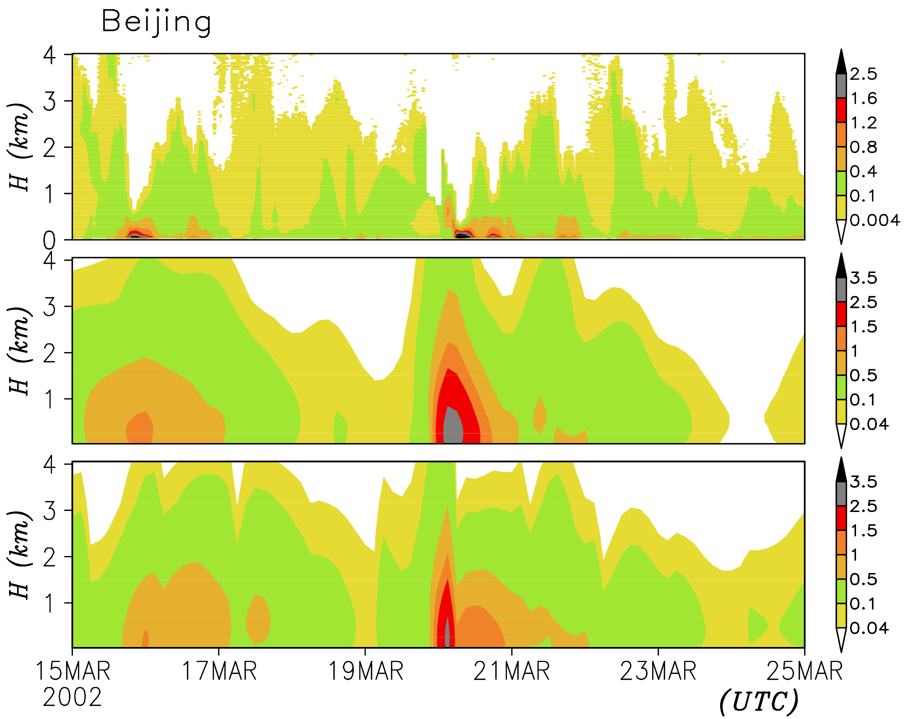

Fig. 6. Comparison of Lidar observed extinction coefficient (top panel, 1/km) and predicted dust density without (middle one, mg/m^3) and with assimilation (bottom one, mg/m^3) in Beijing during 15–24 March 2002.

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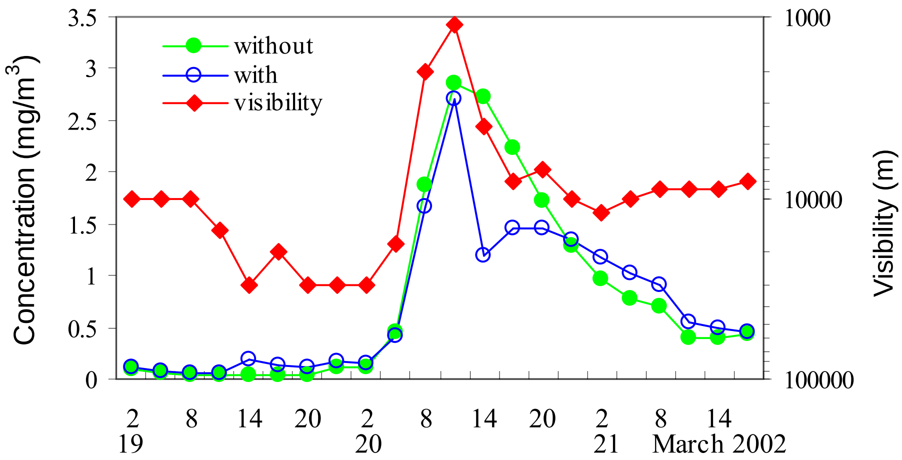

Fig. 7. Time series of surface concentrations of dust aerosols with (blue solid one) and without (green dashed lone) EnKF assimilation and visibility in Beijing during 19–21 March 2002.

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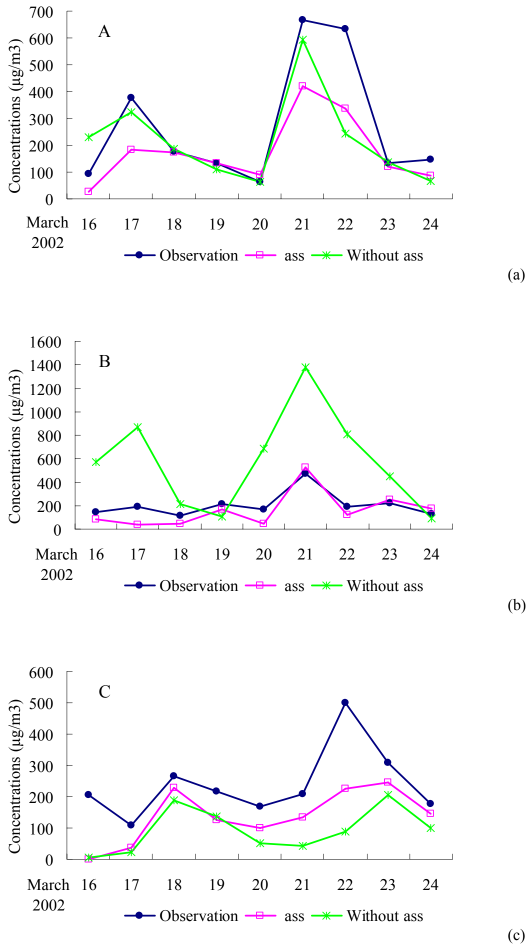

Fig. 8. Comparisons of assimilation results and simulation with observed daily-mean PM_{10} observations at three independent observation stations respectively.

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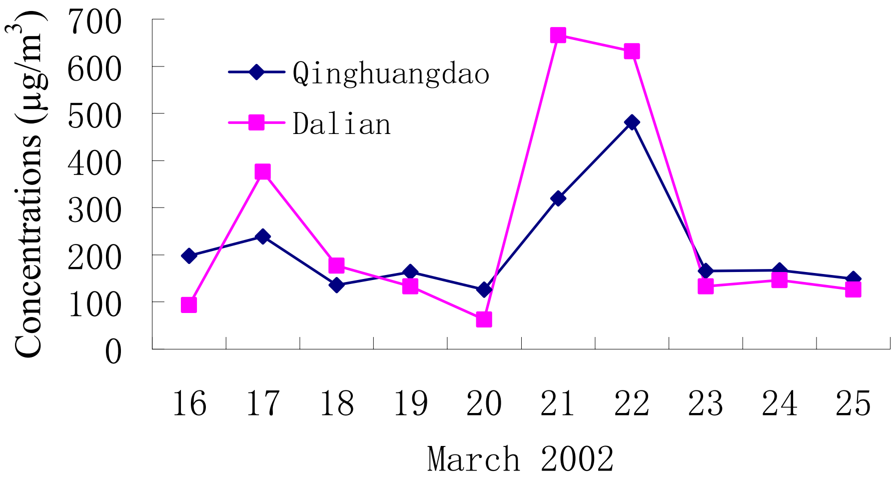

Fig. 9. Variations of observed PM_{10} at Dalian and Qinhuangdao during 16–15 March 2002.

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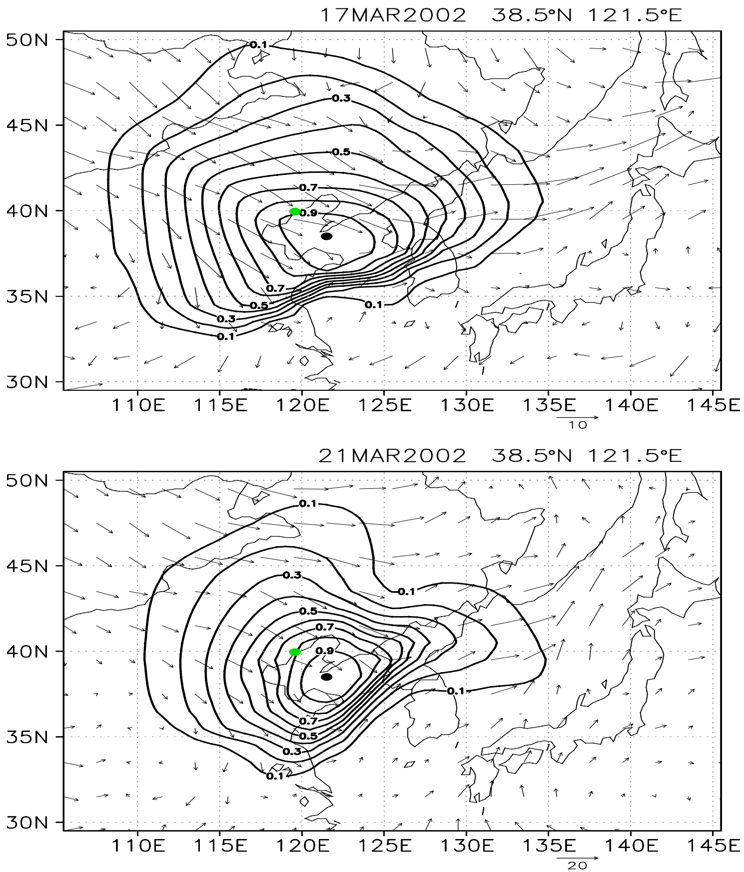

Fig. 10. As in Fig. 2 but with respect to Dalian site on 17 March (top panel) and 21 March (bottom one). The black dot and the green dot are the locations of Dandian and Qinhuangdao respectively.

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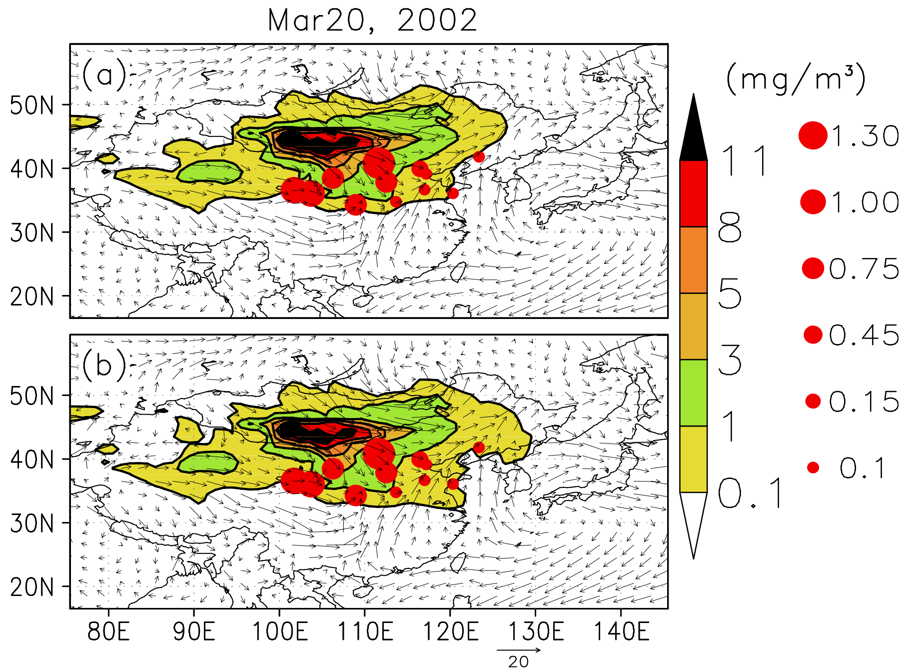

Fig. 11. Surface distribution of dust concentration over East Asia without **(a)** and with **(b)** assimilation on 20 March 2002, respectively. The closed red circles represented the observed PM_{10} levels with unit of mg/m^3.

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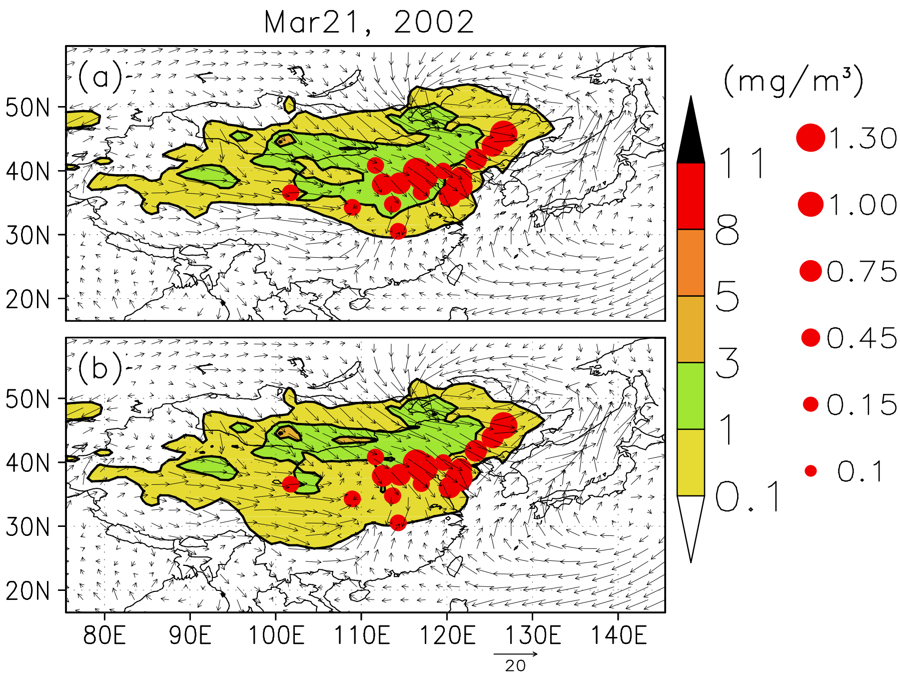

Fig. 12. As in Fig. 11, but on 21 March 2002.

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