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Data assimilation of dust aerosol observations for CUACE/Dust forecasting system

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Abstract

A data assimilation system (DAS) was developed for the Chinese Unified Atmospheric Chemistry Environment – Dust (CUACE/Dust) forecast system and applied in the operational forecasts of sand and dust storm (SDS) in spring 2006. The system is based on a three dimensional variational method (3D-Var) and uses extensively the measurements of surface visibility and dust loading retrieval from the Chinese geostationary satellite FY-2C. The results show that a major improvement to the capability of CUACE/Dust in forecasting the short-term variability in the spatial distribution and intensity of dust concentrations has been achieved, especially in those areas far from the source regions. The seasonal mean Threat Score (TS) over the East Asia in spring 2006 increased from 0.22 to 0.31 by using the data assimilation system, a 41% enhancement. The assimilation results usually agree with the dust loading retrieved from FY-2C and visibility distribution from surface meteorological stations, which indicates that the 3D-Var method is very powerful for the unification of observation and numerical modeling results.

1 Introduction

Several regional dust models have been applied for ACE-Asia field observation periods (Gong et al., 2003b; Huebert et al., 2003; Uno et al., 2006; Zhao et al., 2003) and reasonable simulated results have been reported. Usually, the field campaign results help to evaluate the model and calibrate some parameters in the model. Nevertheless, a current study of the dust model inter-comparison project (DMIP) pointed out the status of current regional dust models when applied to the Asian domain (Uno et al., 2006). It was found that dust transport patterns from the emission source region are usually very similar, but the predicted surface level concentrations sometimes show discrepancies of more than two orders of magnitude. The differences in treating the dust emission schemes, surface boundary data (e.g. soil texture, soil wetness, and land-use data including recent desertification information), and atmospheric models (meteorological and transport models) are speculated as the major source of the discrepancies. This problem will worsen if these models are used in a forecasting mode as the meteorology will be subject to forecasting uncertainties as well. For those reasons, methods for the unification of observations and modeling will play a salient role in improving model forecasting capabilities in any models.

On the other hands, data assimilation is very powerful in improving model forecasting capabilities (Kalnay, 2003). It's based on data statistic analyses and model dynamical evolution. Data assimilation can be used to supply reasonable initial fields to dynamical model. Because of model's uncertainties and observation errors, they will result in the inaccuracy of performance of model. Data assimilation can estimate these errors and balance the errors of observation and model to some degree. Meanwhile, data assimilation can extrapolate information to some areas and some model components even without observation. In addition, the reasonable initial fields offered by data assimilation will make the different components of model in harmony. Therefore a dynamical model system should have a data assimilation system that fits it. There are a variety of algorithms to approach the data assimilation problem (Bennett, 1997; Daley, 1991). The examples of general methods include nudging method, optimal interpolation (OI), 3-dimensional variation (3D-Var). The examples of advanced methods include 4-dimensional variation (4D-Var), extended Kalman Filter and ensemble Kalman Filter (Menard and Chang, 2000; Menard et al., 2000). William et al. (2001) developed a system for forecasting aerosol optical depth (AOD) by coupling a chemical transport model with a system for assimilating satellite retrievals of AOD. Recently, 4D-Var method has come to be applied to chemical transport model (CTMs) for inverse modeling. For example, Hakami et al. (2005) estimated black-carbon emissions over eastern Asia using the adjoint STEM model. Yumimoto and Uno (2006) applied 4D-Var to a CTM and estimated CO emissions over the East Asian region. Most recent developments and results of chemical adjoint are presented by Henze and Seinfeld (2001). However, applications of 4D-Var for CTMs remain limited and in a developmental stage

as they are quite expensive for computation and not easy for system upgrade due to their algorithm depending closely on a model. 3D-Var method was first applied to the assimilation of observational data in 1981 (Bengtsson, 1981). Up to now 3D-Var method plays an important role in studies and operations on weather and climate. Considering the situation of our computer resource and operational requirement, a 3D-Var method was chosen to establish our SDS Data Assimilation System (SDS-DAS).

This paper presents the development of the SDS-DAS and the application of it in spring 2006 SDS operational forecasts in East Asia. Real-time measurements of dust aerosols from surface meteorological stations (visibility and phenomena) and spatial coverage from satellites have been integrated into a unified system for the forecast of dust aerosols through a data assimilation system (DAS).

2 Brief description of the SDS-DAS

Based on the work of Lorenc (1986, 1997) and Barker (2003, 2004), CAMS (Chinese Academy of Meteorological Sciences) developed a three dimensional variational data assimilation system (GRAPES 3D-Var) (Zhang et al., 2004; Zhuang et al., 2005) for the Chinese weather forecast model. This study extends the scheme in GRAPES into a new three dimensional variational data assimilation system (SDS-DAS) to assimilate visibility and satellite retrieval dust loading data to a SDS forecast system – CUACE/Dust. SDS-DAS contains four functional groups: (1) observational data reprocess, (2) observational data merger (statistic analysis), (3) 3D-Var analyses method and (4) an interface to the CUACE/Dust.

2.1 Observational data

Observational data used in SDS-DAS include routine observational visibility data, intensive observational visibility data and satellite remote sensing data. For different data types, different quality control subsystem (QC) was used to admit the data into the DAS.

2.1.1 Satellite retrieval data

The satellite retrieval data are widely used in recent years for their advantages of broad observations and high spatio-temporal resolutions. The satellite data used in this DAS was provided by National Satellite Meteorological Center (NSMC) Based on Chinese FY-2C remote sensing data, NSMC established an automatic identification and real-time dealing-with system for the dust aerosols through combining the separating-window method and spectrum gathering method. A detailed description of the retrieval method was given by Hu et al. (2007)[1]. This data reflecting the dust aerosol column loading was named SDS-IDDI, a dimensionless quantity. The temporal resolution of SDS-IDDI is an hour with a spatial resolution of 5 km×5 km.

Figure 1 illustrates a heavy SDS process during 6–9 April 2006 by FY-2C satellite. Based on the SDS-IDDI, a SDS covers a wide region including the middle and southern parts of Mongolia, the middle of Inner Mongolia and Onqin Daga, also affected the weather at Hetao area of China. At the 6 h on 8 April 2006, it influenced Korean peninsula and the southern areas of Japan. The dust maintained for two days over there. The images of FY-2C satellite present a whole moving process clearly (Figs. 1a and b). In the spring of 2006, there were total 31 SDS processes in the northeastern Asia (Yang et al., 2007[2]) and the satellite always presented clear images of a SDS process (excepting the cloudy cover area). Currently, the DAS adopted SDS-IDDI of 3 and 6 h everyday with the data at 3 h used in the operational forecast system for the prediction efficiency.

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[2]Yang, Y. Q., Hou, Q., Zhou, C. H., Liu, H. L., Wang, Y. Q., and Niu, T.: A Study on Sand/dust Storms over Northeast Asia and Associated Large-Scale Circulations in Spring 2006, Atmos. Chem. Phys. Discuss., submitted, 2007.

2.1.2 Visibility – monitoring data from surface meteorological stations

Because the satellite retrieval data of FY-2C are the products of visible lights, the area that is covered by the clouds is not able to be detected by the remote sensor of the satellite. Therefore, the data assimilation system makes use of the real-time visibility and the weather phenomena observed by surface meteorological stations to obtain more information. The real-time data are distributed by the National Information Center network. Presently, the DAS adopted 3 and 6 h data everyday with the data at 3 h used in the operational forecast system for the prediction efficiency.

Figure 2 shows the two observations from the surface meteorological stations of weather phenomena (Fig. 2a) and the satellite SDS-IDDI (Fig. 2b) at the same time. The results showed that the SDS occurred in the middle and southern part of the Mongolia, the most areas of Inner Mongolia, Gansu province, and Ningxia, as well as in the middle and southern part of Xinjiang, with various intensities, such as floating dust, blowing sand, SDS and severe SDS. However, the satellite images (Fig. 2b) revealed that large areas were covered by the clouds, including Xinjiang, Gansu, the western areas of Inner Mongolia. Therefore SDS-IDDI couldn't reflect SDS information over these regions. Figures 2a and b clearly demonstrated that a complete picture of the SDS distribution should include both the satellite data and surface data.

2.1.3 Data quality control

All observation data come with various errors, including random errors, systematic errors, and gross error. Usually, it's difficult to distinguish them. For a detailed discussion, please refer to Lorenc (1986). Before the data assimilation, data with gross errors should be removed, and the data with systematic errors should be corrected. This data preprocess is called Quality Control (QC). The commonly QC methods include the check of weather consistency and the check of spatial continuity. For the QC of satellite retrieval data, please refer to the article by Hu et al. (2007)[1].

Because of the typical local characteristics of sand-dust weather, the QC in this DAS refers to the check of weather consistency, i.e. checking if the weather phenomena are corresponding to the visibility based on the observation regulations for the sand-dust weather prescribed by WMO. If the data pass the check of weather consistency, it is adopted by DAS. Otherwise, the data are removed.

2.1.4 Estimation of cloudy SDS_IDDI

The satellite retrieval data can only reflect the weather features in clear sky. For the areas covered by the clouds, the surface observations have to be used as complimentary. Due to the advantages and disadvantages of the satellite retrieval data and the surface observation, the DAS adopted both of them. Although these data have different representations, they have the same essentials, so building a regression function for estimating the SDS_IDDI over the cloudy area from the surface visibility is reasonable and feasible. According to Hu et al. (2007)[1], there are correlated relationships between the SDS-IDDI and the visibility which are exponential functions, while different position have the similar function but the coefficients are different, especially for Korea Peninsula (the figures were omitted). These relationships are used to calculate the SDS-IDDI from the visibility during a SDS process over the cloudy area and results in a complete coverage of SDS-IDDI. It should be pointed out that the relationship is location dependant. A database of the fitting coefficients has been generated for use in CUACE/Dust for all regions in Asia from this study.

2.2 SDS 3D-Var assimilation system

2.2.1 3D-Var analysis method

The main task of 3D-Var is to find the minimum of objective function $J(x)$

$$\boldsymbol{J(x)} = \frac{1}{2}\left[(\boldsymbol{x}-x_b)^T\mathbf{B}^{-1}(\boldsymbol{x}-x_b) + (\mathbf{H}(\boldsymbol{x_b})-\boldsymbol{y_o})^T\mathbf{O}^{-1}(\mathbf{H}(\boldsymbol{x_b})-\boldsymbol{y_o})\right] \quad (1)$$

where $\boldsymbol{x}$ is the analysis field of dust concentration, $\boldsymbol{x}_b$ the background field of dust concentration provided by model, $\boldsymbol{B}$ the background error covariance matrix, $\boldsymbol{y}_o$ the observation of dust concentration and $\boldsymbol{O}$ the observation error covariance matrix. $\boldsymbol{H}$ is the observation operator matrix that transfers the variables from model space to observational space. When J goes to the minimum, $\boldsymbol{x}_a$ is the optimized estimate of $\boldsymbol{x}$.

The objective function J is the sum of the two terms. The first term, called background term, represents a departure of the assimilated value $\boldsymbol{x}$ from the first guess field $\boldsymbol{x}_b$, weighted by the background error covariance matrix $\boldsymbol{B}$. The second term, called observation term, represents a departure between simulated and observed values weighted by the observation error covariance matrix $\boldsymbol{O}$. It is obvious that the effect of an assimilation system will rely on how to define $\boldsymbol{B}$ and $\boldsymbol{O}$. The characteristic of $\boldsymbol{B}$ is described in detail later. Generally, it is also very difficult to obtain $\boldsymbol{O}$ exactly and so $\boldsymbol{O}$ is defined as a diagonal matrix, that indicates there is no correlation between observations. Otherwise, it will cause a lot of trouble to the minimization. The minimization of the objective function J is performed through an iterative process using Quasi-Newton limited memory LBFGS scheme (Liu, 1989). Negative values of dust concentration are replaced with zero at the end of analysis.

2.2.2 Background error covariance matrix **B**

The background error covariance matrix **B** is important to the analysis system, which controls how the information from the observation influences the value of model grids nearby the observational position. A statistical harmonious correction is given via **B** to the model grid nearby observational position in order to make sure the dynamical harmony of model variables. However the background error covariance cannot be calculated accurately because the true situation of the atmosphere cannot be known. Usually, the following three methods are used to solve this problem. 1) Observation method or Hollingsworth-Lonnberg (1986); 2) NMC method (Parrish and Derber, 1992); 3) Analysis ensemble method (Fisher, 2001).

In this scheme, the background error covariance is hypothesized separable in horizontal and vertical directions. This means horizontal structure of covariance does not have a relationship with the vertical coordinate. Hollingsworth-Lonnberg (1986) discussed the rationality of this hypothesis. Generally, a Gaussian function is adopted in horizontal. Meanwhile Recursive Filter is used to perform the horizontal transform.

Hypothesizing the distribution of background error covariance is homogeneous and isotropic in horizontal. Therefore, the backgrounds error covariance of any two points under spherical-surface coordinate is a function that only depends on the distance. It is represented by the following function:

$$R(d) = e^{-d^2/2L^2} \tag{2}$$

Where d is the distance between any two points, L is correlation length scale in horizontal.

In the vertical, logarithms function is adopted and EOF is used to solve eigenvalue to perform the vertical transform, the detail discussion refers to Barker et al. (2003).

The correlation structure function in the vertical is:

$$R = (1.0 + kp(\log h_i - \log h_j)^2)^{-1} \tag{3}$$

Where kp is the correlation length scale in the vertical, h_i and h_j are the heights of ith layer and jth layer, respectively.

Through the two transforms in horizontal and vertical directions, the model variables (dust concentration) were transformed to control variables in order to benefit to minimization. When the minimization was finished in control variable space, the inverse matrix was used to transform the control variables to model space. Each stage of the control variable transform is discussed in detail in Barker et al. (2003).

After determining the function for the vertical and horizontal directions, the NMC method (Parrish and Derber, 1992) is used to determine the parameter L for Gaussian function in the horizontal direction. Finally, L=150 km is used in CUACE/Dust system.

2.3 Interface to the CUACE/Dust

The CUACE/Dust system (Gong and Zhang, 2007[3]) was developed based on a size-segregated dust aerosol module CAM (Canadian Aerosol Module) (Gong et al., 2003a) that was coupled into a mesoscale meteorological model - MM5 to conduct real time SDS forecasting in Northeast Asia. The prognostic variables are the dust mass mixing ratio in twelve size bins (Zhou et al., 2007[4]) at all 23 model layers. Since the SDS-IDDI retrieved from FY-2C reflects the dust column loading with a scale 0–30 and the visibility also is an index reflecting the dust strength nearby the surface when a SDS occurs, all the dust mass mixing ratios in 12 size bins at 23 model layers are converted to obtain DM40 (dust matter 40). This DM40 is then integrated in the vertical direction to obtain the column loading, and converted into the same dimensionless scale as the SDS-IDDI, which is performed by the observation operator matrix **H**. After minimizing, the size bin information calculated from background field is used to return the optimized estimate to each size bin. Thus, a new field of dust mass mixing ratio in all 12 size bins at 23 layers is obtained.

3 Assimilation experiments

3.1 One case as a demonstration

In order to investigate the effect of SDS-IDDI and visibility on the analysis result, respectively, 3 types of experiments were conducted with: 1) satellite data only; 2) visibil-

[3]Gong, S. L. and Zhang, X. Y.: CUACE/Dust – An Integrated System of Observation and Modeling Systems for Operational Dust Forecasting in Asia, Atmos. Chem. Phys. Discuss., submitted, 2007.

[4]Zhou, C. H., Gong, S. L., Zhang, X. Y., Wang, Y. Q., Niu, T., Liu, H. L., Zhao, T. L., Yang, Y. Q., and Hou, Q.: Development and Evaluation of an Operational SDS Forecasting System for East Asia: CUACE/Dust, Atmos. Chem. Phys. Discuss., submitted, 2007.

ity data only and 3) both of them. The case chosen for the experiment was the severe SDS occurred on 10 April 2006 (see Fig. 2).

Figure 3a is the analysis field just using SDS-IDDI by the DAS, which agrees with Fig. 2b. Due to the heavy cloud cover, Nanjiang (south Xinjiang) basin did not show any SDS by the satellite. The same happened in middle-west of Gansu province and Mongolia. These missed regions were reported SDS by the surface meteorological stations as was indicated by the analysis field just using visibility data by the DAS (Fig. 3b). Therefore, the meteorological station data provided DAS more information in those area covered by clouds.

Finally, Fig. 3c shows the analysis field using both visibility and SDS-IDDI data by the DAS. Apparently, this result presents a more complete picture of SDS than any of the two observations alone. In the operational forecast using CUACE/Dust, a combination of station and satellite data is used in the DAS.

3.2 Verification of 3D-Var assimilation system

In this 3D-Var assimilation system, SDS_IDDI and visibility data are adopted. The data PM10 was obtained every 5 min by the China SDS Net including 19 stations. This data was used to verify the 3D-Var Assimilation System quantitatively. The 12 size bin dust concentrations are calculated by the model with and without assimilation system. Through summing up the mass in the size bin 1–8, PM10 can be obtained for the background and analysis. Figure 4a gives the mean standard absolute deviation of O-B (observation- background) and O-A (observation-analysis), 1 March–31 May 2006. Most of dots are above the diagonal line indicating a reduction of standard absolute deviation through assimilation. Figure 4b gives the mean bias of O-B and O-A, 1 March–31 May 2006. All of them reveal the error statistics characteristics before and after analysis. It can be observed that most of the verification stations obtain a reduction of both standard deviation and bias as a result of the analysis.

4 Impacts of assimilation on CUACE/Dust forecasting

4.1 Case studies of SDS forecast improvements by DAS

In spring 2006, the CUACE/Dust was used as the operational dust forecasting system in China with DAS. During this period, more than 31 SDS processes were recorded (Yang et al., 2007[2]), five of which were rated as severe SDS. CUACE/Dust-DAS always had a good performance in each case.

Figure 5 shows the forecasting results of the 5–9 April severe SDS with (Fig. 5b) and without (Fig. 5a) the DAS. Comparing these two results, it can be found that DAS has a very important influence on the results of CUACE/Dust not only on the intensity but also on the position and areas covered. In this case, the SDS transported to Korea and the south part of Japan on 8 April 2006 and maintained there for 2 days. The forecasts with DAS agreed with this fact (Fig. 5b), but the forecasts without DAS couldn't predict this phenomenon (Fig. 5a). This demonstrates that the DAS plays a very important role for forecasting the SDS in the downwind areas far away from the source regions.

The DAS also improved the forecasts at the source regions. Figure 6 shows a case on 9–11 April 2006 where a severe SDS occurred in the source regions. Comparing Figs. 6a and b, it can be found that the forecasts with DAS agreed with the surface observations while the forecasts without DAS were much weaker and missed a lot of regions, especially in the middle part of Inner Mongolia and south part of Outer Mongolia. This case illustrated that the DAS also plays a very important role when the dust emission is not accuracy in the areas close to the source regions.

The final case was for a SDS that was over-predicted by the CUACE/Dust without the DAS initial conditions (Fig. 7). A regular strength SDS occurred on 22 April 2006. Comparing these two predictions (Figs. 7a and b), it can be found that DAS has revised the results of CUACE/Dust forecasts not only to the intensity but also to the positions and areas covered. In this case, the CUACE/Dust without DAS forecasted a SDS would arrive in Beijing and Tianjin at 09:00 GMT, 22 April 2006. With the DAS the forecast showed that a SDS would just arrive in northern Hebei province where is north to Beijing, which agreed with surface observations. Another revision was made for North-East China and Shandong province.

4.2 Forecast verification – Threat Score (TS)

Threat score (TS) is a statistical method to verify forecast quality prescribed by WMO. For the entire season of spring 2006, the CUACE/Dust forecasting results were verified against observations by a TS system (Wang et al., 2007[5]). Figure 8 shows a comparison of the daily TS (Yes/No forecast) for the season with and without DAS in CUACE/Dust. For most SDS processes, for example, 8–14 March , 23–25 March , 5–9 April , 20–25 April, 2–4 May , 29–30 May etc., the TS with DAS are much better than those without DAS. The seasonal mean TS increased from 0.22 without DAS to 0.31 with DAS, a 41% enhancement.

5 Conclusions

A DAS was developed within the frame work of CUACE/Dust to use the visibility and satellite retrieval dust loading data for the SDS forecasts. Sensitivity tests show that both satellite retrieval data and surface observation (visibility and phenomena) have the same importance for the SDS forecasts. A combination of them provided the best performance. A contrast analysis revealed that the 3D-Var method has made a major improvement for the capability of the model in forecasting short-term variability in the spatial distribution and intensity of dust concentration, especially in those areas far from the source regions. The TS increased 41% in spring 2006 by the DAS to reach a seasonal average of 0.31.

[5]Wang, Y. Q., Zhang, X. Y., Zhou, C. H., Hu, X. Q., Liu, H. L., Niu, T., and Yang, Y. Q.: Surface observation of sand and dust storm in East Asia and its application in CUACE/Dust forecasting system, Atmos. Chem. Phys. Discuss., submitted, 2007.

However, a major component missing from the observations is the near real-time vertical profiles of the SDS. Surface lidar can provide vertical information for the data assimilation system, which should help to correct the vertical structures. In the future as more lidar observations become available and real time in Asia, lidar data will be adopted in the DAS.

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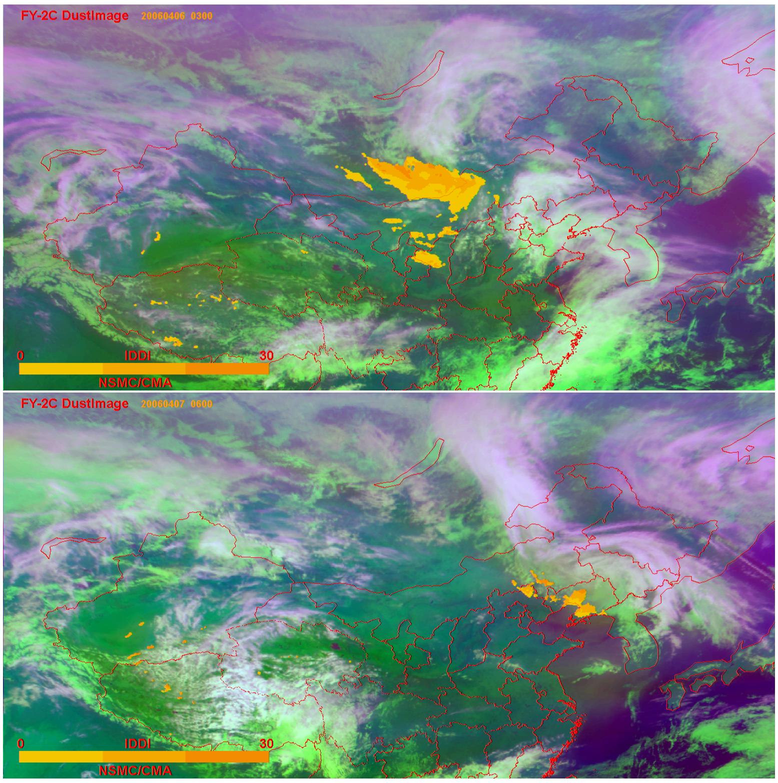

Fig. 1. Retrieved SDS_IDDI (yellow area) from Chinese geostationary satellite FY-2C **(a)** at 03:00 GMT on 6 April 2006 and **(b)** at 06:00 GMT on 7 April 2006.

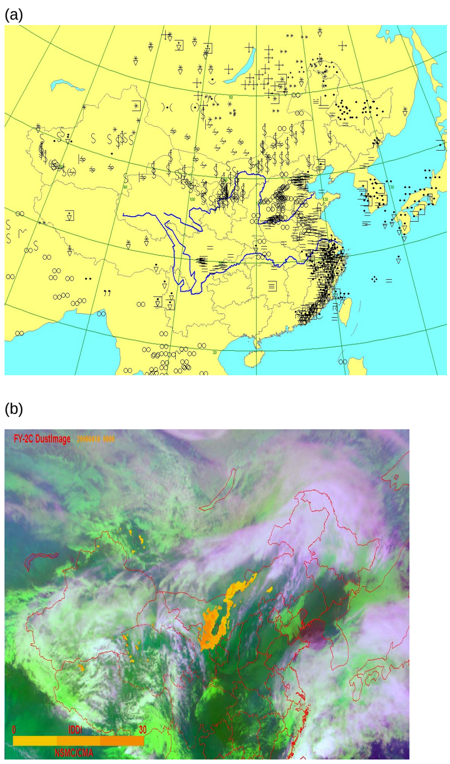

Fig. 2. **(a)** Observations of SDS phenomena from the surface meteorological stations and **(b)** SDS_IDDI (yellow area). The time is 06:00 GMT on 10 April 2006. The symbols of “S”, “S”, “S”, “S” indicate floating dust, blowing sand, SDS, severe SDS, respectively, obtained from surface meteorological stations.

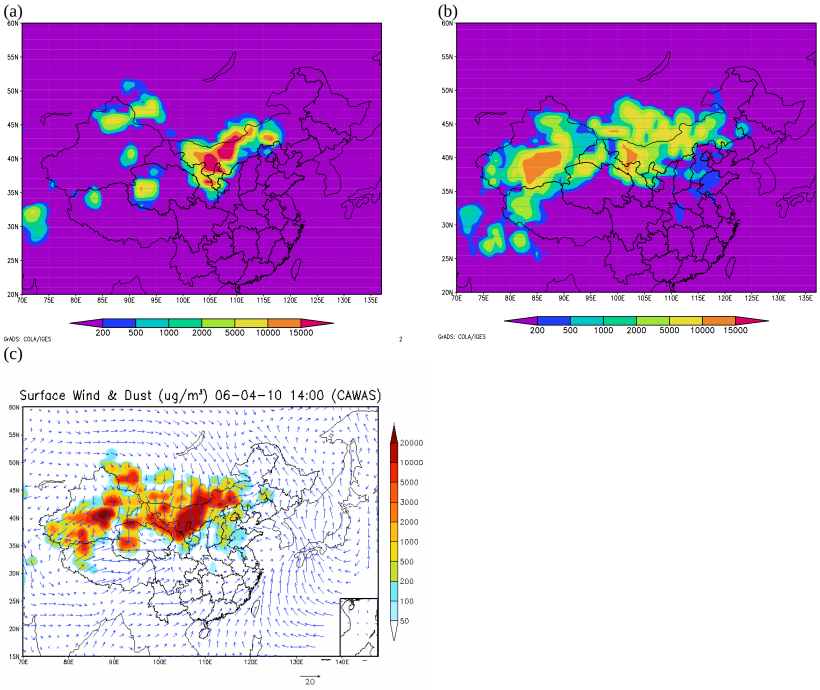

Fig. 3. Analysis dust concentration results at 06:00 GMT on 10 April 2006 for three types of DAS experiments by using **(a)** only SDS_IDDI, **(b)** only visibility and (3) both SDS_IDDI and visibility.

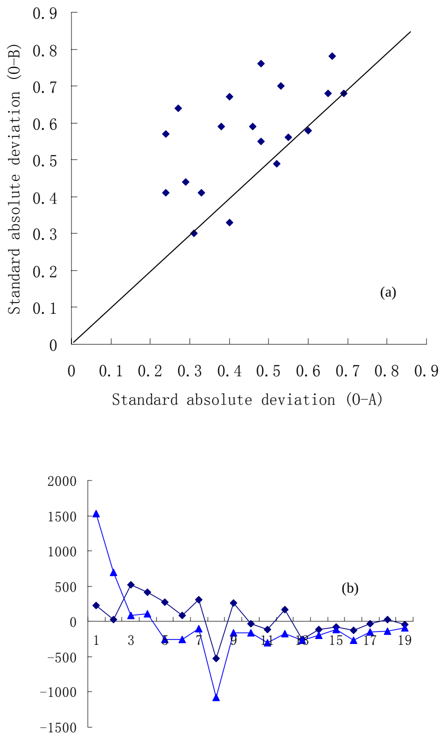

Fig. 4. Verification of 3D-Var assimilation system. **(a)** mean standard deviation of O-B and O-A, 1 March–31 May 2006. **(b)** mean bias of O-B and O-A, 1 March–31 May 2006. The line with triangle is O-B, the line with diamond is O-A.

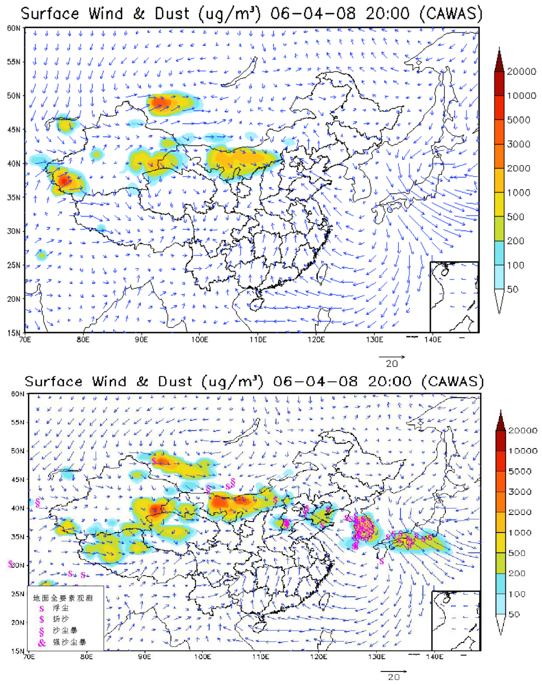

Fig. 5. The forecasted dust concentrations by CUACE/Dust using **(a)** an ideal initial conditions and **(b)** a DAS generated initial conditions and with surface observations. Case 8 April 2006. The symbols of "**S**", "**$**", "**§**", "**&**" indicate floating dust, blowing sand, SDS, severe SDS respectively, obtained from surface meteorological stations.

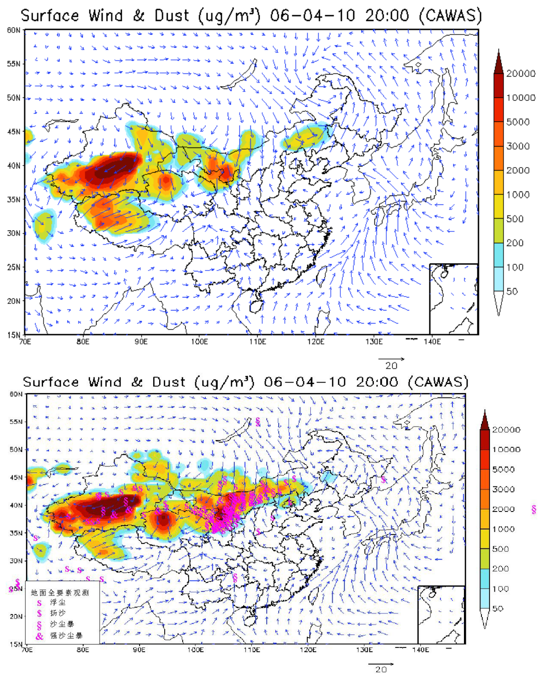

Fig. 6. The forecasted dust concentrations by CUACE/Dust using **(a)** an ideal initial conditions and **(b)** a DAS generated initial conditions and with surface observations. Case 10 April 2006. The symbols of "**S**", "**$**", "**§**", "**&**" indicate the same as Fig. 4.

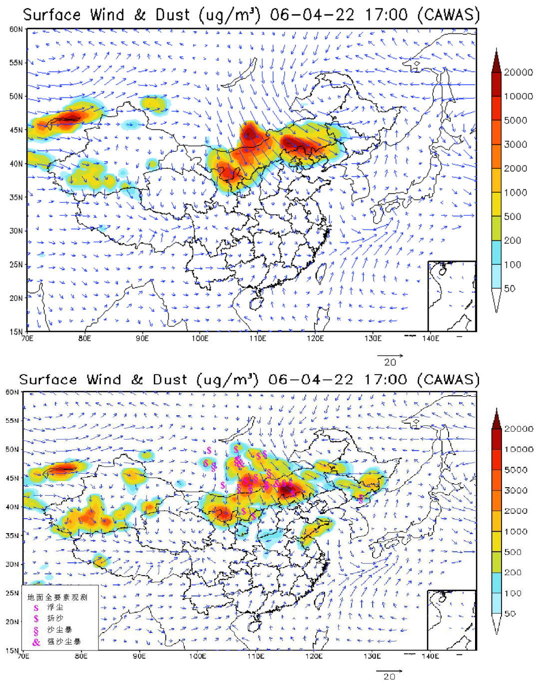

Fig. 7. The forecasted dust concentrations by CUACE/Dust using **(a)** an ideal initial conditions and **(b)** a DAS generated initial conditions and with surface observations. Case 22 April 2006. The symbols of "**S**", "**$**", "**§**", "**&**" indicate the same as Fig. 4.

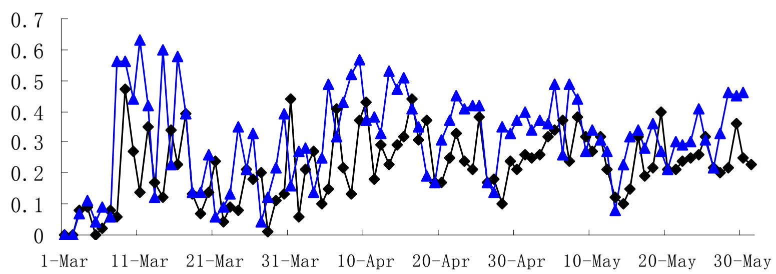

Fig. 8. The daily Threat Score during the period of spring 2006. The line with triangle is daily TS with DAS in CUACE/Dust. The line with diamond is daily TS without DAS in CUACE/Dust.