The Effects of Snow Cover and Soil Moisture on Asian Dust: II. Emission Estimation by Lidar Data Assimilation

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Abstract

This paper is the second of a series that describes the effects of snow cover and soil moisture on Asian dust during spring. Whereas the first paper in this series discussed the importance of snow cover and soil moisture estimation, here, we focus on the correctness of the dust emission intensity results based on data assimilation under the assumption that simulation models yield errors in snow cover and soil moisture. We utilized global satellite lidar measurements and a four-dimensional ensemble Kalman filter to optimize the dust emission simulation. The data assimilation results were evaluated by a comparison with independent ground-based lidar measurements. The data assimilation procedure resulted in an increase in the dust emission in the Gobi region during the dust event from March 25 to April 3, 2007, and it improved the analysis of dust concentrations in the leeward region. Without data assimilation, the dust concentrations were underestimated owing to the wet surface conditions of the dust source region. This paper confirms that the improvement of snow cover and soil moisture estimation is important in the analysis of Asian dust levels, and it demonstrates that data assimilation is a powerful tool that can contribute to such improvement.

1. Introduction

The important influence of dust on the global environment and on human activities is increasingly recognized. There is a growing need to analyze and forecast the distribution of aeolian dust. Numerical simulation is a widely used tool in dust aerosol analyses and forecasts (e.g., Uno et al. 2006; Benedetti et al. 2009). A numerical simulation of this sort is composed of several components: dust emission, deposition, advection, convection, and aging processes. Among these components, emission estimation is critical for dust analyses and forecasts because major dust plumes are observed only when sporadic dust outbreaks occur in limited areas (Kurosaki and Mikami 2003). Consequently, accurate estimation of dust emission is important for successful dust simulation. Generally, we have two choices to improve dust emission accuracy: one is to construct sophisticated dust aerosol models (e.g., Tanaka et al. 2011), and the other is to utilize data assimilation (e.g., Yumimoto et al. 2008; Sugimoto et al. 2010). In particular, state-of-the-art data assimilation schemes, such as the ensemble Kalman filter (EnKF) and the four-dimensional variational method (4D-Var), are able to optimally control not only state variables of the model but also poorly known parameters of the model (cf., Evensen 2006). This capability allows data assimilation to optimize both the aeolian dust concentration (state variables) and dust emission factors (poorly known parameters) simultaneously.

In Asian dust source regions, as Tanaka et al. (2011) argued, the influence of snow cover and soil moisture on dust emission intensity is critical. Tanaka et al. (2011) demonstrated the importance of snow cover and soil moisture using a model and PM10 observations, and indicated that the effect of vegetation growth on dust emission becomes pronounced only in late spring while Sugimoto et al. (2010) argued only the importance of vegetation growth. Sugimoto et al. (2010) ignored the effect of snow cover and soil moisture because their simulation results were not dependent on the soil moisture content.

Generally, it is difficult for simulation models to estimate snow cover ratios and soil moisture content. Consequently, Asian dust simulation does not yield good performance especially for early spring. The inaccuracy of dust analysis also degrades dust forecast performance because the analysis is used to furnish initial conditions for the forecast. In this case, the snow cover ratios and soil moisture content are expected to be poorly known parameters of the simulation model. However, this situation represents an excellent opportunity for data assimilation to optimize these parameters and to demonstrate its superior performance. Whereas Tanaka et al. (2011) pointed out the importance of snow cover and soil moisture estimation, we focused on the correctness of dust emission intensity using data assimilation with the assumption that simulation models yield errors in snow cover ratios and soil moisture content. This paper is the second in a series describing the effects of snow cover and soil moisture on Asian dust simulation, following the initial paper by Tanaka et al. (2011). In this study, we utilized global satellite lidar measurements and the four-dimensional EnKF data assimilation system developed by Sekiyama et al. (2010) to obtain corrections for Asian dust emission intensity for the spring of 2007. The impact of the corrections on the Asian dust simulation was then evaluated by a comparison with independent ground-based lidar measurements. It was shown that data assimilation can yield efficient optimization for the sporadic phenomena that constitute a dust outbreak.

2. Methodology

Sekiyama et al. (2010) developed a data assimilation system for dust and sulfate aerosols. Their system couples a global aerosol model with EnKF. Their framework was utilized throughout this study. Although many EnKF implementation methods have been and continue to be developed, a four-dimensional Local Ensemble Transform Kalman Filter (4D-LETKF; cf., Hunt et al. 2007) was applied to this system. The four-dimensional expansion allows the EnKF to assimilate asynchronous observations of the past and the future by analogy with 4D-Var. The module for the 4D-LETKF was provided by the Numerical Prediction Division of the Japan Meteorological Agency (JMA), who experimentally applied the 4D-LETKF system to numerical weather prediction models (e.g., Miyoshi and Yamane 2007; Miyoshi et al. 2007). In this study, the 4D-LETKF module was further improved by adding a model bias correction process using the method of Dee and da Silva (1998) and Carton et al. (2000) in a way similar to that of the analyses of Li et al. (2009). The ensemble size was set to 32 members; the localization scale was horizontally 3000 km; the multiplicative spread inflation factor was 20%; the dust emission flux was additionally perturbed by adding random Gaussian noise (25% deviation); the parameter \( \alpha \) of Dee and da Silva (1998) was 0.75, and the parameter \( \mu \) of Carton et al. (2000) was 0.9; the time window was 48 hour with 1-hour intervals; and the analysis was obtained every 24 hours. The initial ensemble spreads were generated by adding random Gaussian noise to the initial fields at the beginning of data assimilation experiments.

This 4D-LETKF system was integrated with the on-line global aerosol model MASINGAR (Tanaka et al. 2003; Tanaka...
and Chiba 2005). MASINGAR simulates sulfate aerosol, sea-salt aerosol (partitioned into 10 size bins), dust aerosol (partitioned into 10 size bins), organic aerosol, and black carbon aerosol. It has a $2.8^\circ 	imes 2.8^\circ$ horizontal resolution (T42 spectrum truncation) and 30 vertical layers in a hybrid sigma-pressure coordinate from the earth’s surface to the stratopause (7 layers below 800 hPa and 15 layers above 150 hPa). The meteorological field in MASINGAR was nudged to a 6-hour interval reanalysis of JMA using a Newtonian relaxation with 18-hour $\tau$. This model was also used by Tanaka et al. (2011) with the same conditions except for their higher horizontal resolution. In MASINGAR, the dust emission flux $F_{ij}$ of the $k$-th size bin is calculated at each surface grid $(i,j)$ as follows (Tanaka and Chiba 2005):

$$F_{ij} = C_A (w,v) f_k(u^{*},v^{*}),$$

where $C$ is a global tuning factor universally set to $1 \times 10^{-3}$; $A$ is a function of the ground-surface conditions (i.e., $w$ is the soil moisture content, $s$ is the snow cover ratio, and $v$ is the vegetation cover ratio) that ranges between 0 and 1; and $f_k$ is the dust emission flux estimated by a wind erosion model function of surface friction velocity $u^*$. Here, $u^{*}$, $v^{*}$ is the threshold surface friction velocity and is a function of the soil moisture content. In this study, we assumed that dust analysis is negatively influenced by uncertainties in snow cover and soil moisture estimation. The snow cover ratio and soil moisture content at each grid were therefore fixed at 0 to optimize the effects of these two parameters in the 4D-LETKF data assimilation as follows:

$$\Phi_{ij} = C \varepsilon_{ij} A, \quad v_f(u^{*},v^{*}), \quad u^* > u_c,$$

where $\Phi_{ij}$ is the optimized dust emission flux, and $\varepsilon_{ij}$ is a scaling factor controlled by the data assimilation that ranges between 0 and 1. $A$ does not depend on $w$, and $s$; $u_c$ does not depend on $w$. If the scaling factor $\varepsilon$ is set to 1, this equation represents the dust emission flux for completely dry surface conditions. Figure 1 shows an example of $F_{ij}$ and $\Phi_{ij}$ in the spring of 2007 under the condition that $\varepsilon$ is universally fixed at 1.

With this system, we performed data assimilation to utilize satellite aerosol observations made by the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) mission (Winker et al. 2007) in a mode of data screening and preprocessing similar to that in Sekiyama et al. (2010). The assimilated contents were the total attenuated backscattering coefficients at 532 and 1064 nm and the volume depolarization ratios at 532 nm obtained from the CALIPSO/CALIOP Level 1B dataset assuming that they have 20% observation errors ($1 \times 10^{-1} \text{sr}^{-1} \text{km}^{-1}$ at the minimum). The three-month data assimilation experiment was initiated at 00:00 UTC on 1 March and was terminated at 00:00 UTC on 1 June 2007. The control variables for the data assimilation were the aeolian dust concentrations (10 size bins), sulfate aerosol concentrations, and surface dust emission flux scaling factor $\varepsilon_{ij}$. Other aerosols and flux indexes were not controlled. In this experiment, horizontal winds of the JMA 6-hourly reanalysis were also assimilated (assuming observation error $= 1 \text{ m s}^{-1}$) simultaneously with aerosol lidar observations to utilize information on the covariance of wind directions and aerosol concentrations.

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Fig. 1. Dust emission flux simulated by MASINGAR; all 10 size bins were accumulated for one month. Dark red indicates relatively high values. (a) $F_{ij}$ in March 2007; soil moisture, snow cover, and vegetation cover were varied. (b) $\Phi_{ij}$ in March 2007; vegetation cover was varied, but soil moisture and snow cover were fixed to 0 and $\varepsilon = 1$. (c) $F_{ij}$ in May 2007; soil moisture, snow cover, and vegetation cover were varied. (d) $\Phi_{ij}$ in May 2007; vegetation cover was varied, but soil moisture and snow cover were fixed to 0 and $\varepsilon = 1$.

Fig. 2. (Upper) Dust emission flux during a dust event from March 25 to April 3, 2007; (a) $F_{ij}$ simulated by MASINGAR without data assimilation, (b) $\Phi_{ij}$ optimized by the data assimilation with CALIPSO/CALIOP data, and (c) difference between $F_{ij}$ and $\Phi_{ij}$. (Lower) Dust emission flux during a dust event from May 21 to May 30, 2007; (d) $F_{ij}$ simulated by MASINGAR without data assimilation, (e) $\Phi_{ij}$ optimized by the data assimilation with CALIPSO/CALIOP data, and (f) difference between $F_{ij}$ and $\Phi_{ij}$. All 10 size bins were accumulated during the dust event period. Red (blue) shades in the flux difference maps indicate that the $\varepsilon$-optimized dust emission is stronger (weaker) than MASINGAR-simulated dust emission.
This simultaneous assimilation prevented model divergence. Here the initial ensemble mean of horizontal winds was provided by Newtonian relaxation nudging, and only the initial ensemble spreads were made by the 4D-LETKF. This method is called one-way variable localization (cf., carbon dioxide analysis performed by Kang 2009).

3. Results and discussion

As mentioned by Tanaka et al. (2011), typical instances of Asian dust outbreak events were frequently observed during spring 2007. One of these severe dust storms arose in the Gobi region at the end of March 2007. The region was supposed to have been somewhat wet and occasionally covered with snow. This event represents an excellent test case for estimating the impacts of snow cover and soil moisture on dust emission. The influence of wetness can be seen in Figs. 1a and 1b; namely, a substantial increase in dust emission was calculated in the case of hypothetically dry conditions at the end of March. In contrast, another severe dust storm arose at the end of May 2007 in which the dust source region was supposed to be much drier than it was in March. Consequently, the difference between Fig. 1c (under normally simulated conditions) and Fig. 1d (under hypothetically dry conditions) is very small. These two events were simulated by MASINGAR and were optimized by the data assimilation as shown below. One case is for the period March 25 to April 3, and the other is for May 21 to May 30.

The upper panels of Fig. 2 illustrate the dust event from March 25 to April 3. Figure 2a shows the dust emission flux of the MASINGAR simulation without data assimilation. Figure 2b shows the dust emission flux optimized by the data assimilation. Evidently, the data assimilation increases the estimated dust emission over the source areas of Asian dust. The increase does not have a uniform distribution, as shown in Fig. 2c, which displays the difference between Figs. 2a and 2b. As discussed by Tanaka et al. (2011), MASINGAR underestimates the dust emission flux in early spring in the Gobi region owing to the overestimation of soil moisture. The data assimilation modifies the flux underestimation through the optimization of the parameter $\varepsilon$ to decrease the soil moisture content. In contrast, the data assimilation decreases the dust emission over the source areas of Asian dust during the period from May 21 to May 30, as shown in the lower panels (Figs. 2d, 2e, and 2f). MASINGAR, however, overestimates the dust emission flux even in March sometimes in some areas, and vice versa in May. Consequently, the dust emission was not uniformly increased or decreased by this adjustment.

These data assimilation analyses are based on the assumption that the flux simulation error is caused by the snow cover and soil moisture overestimation in the model. However, Sugimoto et al. (2010) reasoned that the flux underestimation for spring 2007 was caused by the vegetation growth error and that the influence of soil moisture uncertainty was negligible. Nevertheless, if we focus on the Gobi region, the spatial pattern of the emission difference shown in Fig. 2c has a general resemblance to the distribution of the dust emission corrected by Sugimoto et al. (2010, Fig. 1c therein) using 4D-Var data assimilation. This spatial pattern in the Gobi region also agrees qualitatively with the result of the classic inverse analysis by Maki et al. (2011).

Comparison with independent observations is indispensable to verify model simulations and data assimilations. Figure 3a illustrates the extinction coefficients for dust aerosol at 532 nm measured at the Nagasaki observatory in western Japan near the Korean Peninsula from 1 to 31 March 2007. The observatory belongs to the East Asian lidar network operated by the National Institute for Environmental Studies (NIES) of Japan (Shimizu et al. 2004). Virtual extinction coefficients of the same period (Fig. 3b) and location were derived from the results of the MASINGAR simulation without data assimilation (Fig. 3b) and the CALIPSO/CALIOP data assimilation (Fig. 3c). Evidently, the MASINGAR simulation underestimates the dust concentration owing to the overestimation of soil moisture at the dust source areas as shown

![Fig. 3. Comparison of the extinction coefficients for dust aerosol at 532 nm at the Nagasaki observatory in western Japan near the Korean Peninsula from March 1 to March 31, 2007. The X-axis shows the date. Each tick mark indicates 00:00 UTC. The Y-axis shows the altitude. (a) NIES lidar measurements independent of the data assimilation, (b) MASINGAR simulation results without data assimilation, and (c) CALIPSO/CALIOP data assimilation results.](image)

![Fig. 4. Comparison of the extinction coefficients for dust aerosol at 532 nm at the Nagasaki observatory in western Japan near the Korean Peninsula from May 1 to May 31, 2007. The X-axis shows the date. Each tick mark indicates 00:00 UTC. The Y-axis shows the altitude. (a) NIES lidar measurements independent of the data assimilation, (b) MASINGAR simulation results without data assimilation, and (c) CALIPSO/CALIOP data assimilation results.](image)
in Fig. 1a and cannot reproduce dust plumes at all. In contrast, the data assimilation quantitatively reproduces the dust plumes of March 6–15 and 25–31. This agreement with the independent NIES data clearly indicates that the data assimilation works well and that its optimization is reliable.

In contrast, completely different characteristics can be seen in the analysis for May. Figure 4 illustrates extinction coefficient from May 1 to May 31, 2007. The difference between the MASINGAR simulation (Fig. 4b) and the data assimilation (Fig. 4c) is relatively small. Both results demonstrate good agreement with the independent NIES lidar measurements (Fig. 4a). The MASINGAR simulation slightly underestimated the dust concentration, especially in the boundary layer, whereas the data assimilation slightly underestimated the dust concentration. The overall improvement by this MASINGAR simulation for May 2007 is possibly a result of the uncertainties regarding vegetation growth, as Sugimoto et al. (2010) reasoned.

As seen in Figs. 3 and 4, details of the data assimilation results do not completely coincide with the independent observations although the data assimilation results were improved from the non data assimilation results. These discrepancies are attributed to other than the uncertainties of snow cover and soil moisture. Lin et al. (2008) pointed out that wind speed uncertainty significantly impacts on the Asian dust simulation, and the error of deposition rates are also the source of model biases. These model uncertainties are not corrected by the data assimilation in this study.

4. Conclusion

We utilized CALIPSO/CALIOPI measurements and the 4D-LETKF data assimilation system to optimize the emission flux of Asian dust during spring 2007 with the assumption that the dust emission flux error is caused by the snow cover and soil moisture uncertainties in the model. The data assimilation procedure increased the simulated dust emission in the Gobi region during the dust event from March 25 to April 3 and dramatically improved the analysis of aeolian dust concentrations in the downstream area. Without data assimilation, the dust concentrations were extremely underestimated owing to the wet surface conditions of the dust source regions, as Tanaka et al. (2011) mentioned. Tanaka et al. (2011) reasoned that accurate information about snow cover and soil moisture is critical for the performance of Asian dust simulations for early spring. Their conclusion was successfully confirmed by the data assimilation results. The improvement of such hydrological estimation procedures is evidently important in Asian dust analysis and prediction, and data assimilation is a powerful tool that can contribute to such improvement.

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