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Forecasting of Asian dust storm that occurred on May 10–13, 2011, using an ensemble-based data assimilation system☆

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ABSTRACT

An ensemble-based assimilation system that used the MASINGAR mk-2 (Model of Aerosol Species IN the Global AtmospheRe Mark 2) dust forecasting model and satellite-derived aerosol optical thickness (AOT) data, processed in the JAXA (Japan Aerospace Exploration Agency) Satellite Monitoring for Environmental Studies (JASMES) system with MODIS (Moderate Resolution Imaging Spectroradiometer) observations, was used to quantify the impact of assimilation on forecasts of a severe Asian dust storm during May 10–13, 2011. The modeled bidirectional reflectance function and observed vegetation index employed in JASMES enable AOT retrievals in areas of high surface reflectance, making JASMES effective for dust forecasting and early warning by enabling assimilations in dust storm source regions. Forecasts both with and without assimilation were validated using PM_{10} observations from China, Korea, and Japan in the TEMM WG1 dataset. Only the forecast with assimilation successfully captured the contrast between the core and tail of the dust storm by increasing the AOT around the core by 70–150% and decreasing it around the tail by 20–30% in the 18-h forecast. The forecast with assimilation improved the agreement with observed PM_{10} concentrations, but the effect was limited at downwind sites in Korea and Japan because of the lack of observational constraints for a mis-forecasted dust storm due to cloud.

Introduction

Asian dust, which is a major aerosol during spring in Japan, often degrades air quality, not only in its upwind source regions such as the Gobi and Taklamakan deserts, but also in the downwind regions of China, Korea, and Japan. Park and Lee (2004) described severe dust storms that occurred in 2002 during which PM_{10} concentrations exceeded 1000 $\mu g/m^3$ at most monitoring sites in South Korea, forcing most airports and elementary schools to close.

To mitigate the impact of severe dust storms, it is crucial to develop a forecasting and early warning system for dust events. Operational dust forecasting systems include the Model of Aerosol Species IN the Global AtmospheRe Mark 2 (MASINGAR mk-2; Yukimoto et al., 2011, 2012; http://www.jma.go.jp/en/kosafcst/) of the Japan Meteorological Agency (JMA), Asian Dust Aerosol Model version 2 (ADAM2; Park, Choe, Lee, Park, & Song, 2010; http://www.kma.go.kr/eng/weather/asiandust/forecastchart.jsp) of the Korea Meteorological Administration, Chinese Unified Atmospheric Chemistry Environment for Dust (CUACE/Dust; Gong & Zhang, 2008; http://eng.weather.gov.cn/dust/) of the China

Abbreviations: ADAM2, Asian dust aerosol model version 2; AD-Net, Asian dust and aerosol lidar observation network; AERONET, aerosol robotic network; AGCM, atmospheric general circulation model; AI, aerosol index; AOT, aerosol optical thickness; BRF, bidirectional reflectance function; CFORS, chemical weather forecasting model system; CUACE/Dust, Chinese unified atmospheric chemistry environment for dust; DMIP, dust model intercomparison project; EORC, Earth Observation Research Center (Japan); EVI, enhanced vegetation index; JASMES, Japan aerospace exploration agency satellite monitoring for environmental studies; JAXA, Japan Aerospace Exploration Agency; JMA, Japan Meteorological Agency; LETKF, local ensemble transform Kalman filter; MASINGAR mk-2, model of aerosol species in the global atmosphere mark 2; MODIS, moderate resolution imaging spectroradiometer; MRI, Meteorological Research Institute (Japan); NAAPS, navy aerosol analysis and prediction system; NIES, National Institute for Environmental Studies (Japan); NDVI, normalized difference vegetation index; OMI, ozone monitoring instrument; SYNOP, surface synoptic observations; TEMM, tripartite environmental ministers meeting; WMO, World Meteorological Organization.

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Meteorological Administration, Navy Aerosol Analysis and Prediction System (NAAPS; Christensen, 1997; http://www.nrlmry.navy.mil/aerosol/) of the U.S. Naval Research Laboratory, Chemical weather FORecasting model System (CFORS; Uno et al., 2003; http://www-cfors.nies.go.jp/~cfors/) of the Research Institute for Applied Mechanics, Kyushu University, and the National Institute for Environmental Studies (NIES) of Japan. Useful information about dust storms is provided by these models; however, large variations and uncertainties remain. Simulation results from eight dust models were compared in the Dust Model Intercomparison Project (DMIP; Uno et al., 2006). The report stated that simulated dust emissions could differ by a factor of 10. Furthermore, the AeroCOM project (Textor et al., 2006) estimated diversities of dust emission and burden of 49% and 40% from the simulation results of 16 aerosol models.

Recently, researchers and scientists have enhanced the sophistication of some models to reduce such uncertainties. For example, Kang, Tanaka, and Mikami (2014) developed a new dust emission scheme that considers dead leaves that grew during the previous year. Park et al. (2010) modified their model using new land surface information, i.e., World Meteorological Organization (WMO) surface report and spot/vegetation NDVI (Normalized Difference Vegetation Index). In addition to the development of new methods and the use of new data over the last decade, one of the most important advances in dust simulation has been the application of data assimilation (e.g., Benedetti et al., 2009; Dai, Schutgens, Goto, Shi, & Nakajima, 2014; Wang, Barker, Snyder, & Hamill, 2008; Yumimoto & Takemura, 2015; Yumimoto et al., 2008). For example, Niu et al. (2008) applied a three-dimensional variational method to CUACE/Dust to assimilate surface visibility measurements and the dust-loading index retrieved from satellite data. Lin, Zhu, and Wang (2008) developed an assimilation system for dust data using an ensemble Kalman filter and a regional dust transport model, which they used to estimate the impact of the assimilation of in situ PM_{10} observations on dust forecasts. Sekiyama, Tanaka, Shimizu, and Miyoshi (2010) incorporated an ensemble Kalman filter into MASINGAR and assimilated vertical aerosol profiles from spaceborne lidar (CALIPSO) data. Lee, Ha, Lee, and Chun (2013) applied an optical interpolation method to ADAM2 to assimilate PM_{10} observations. Zhang, Campbell, Hyer, Reid, and Westphal (2014) evaluated the impact of single- and multi-sensor data assimilations on forecast skill. These studies suggest that although data assimilation is a powerful tool in dust forecasting, many challenges remain. For example, Sandu and Chai (2011) discussed the challenges of chemical data assimilation and they highlighted that one possible future direction involves the coupling of meteorological and air quality forecasting with a data assimilation system. Another challenge is the optimization of dust emissions because the evaluation of intensity, timing, and distribution of dust emissions has a direct effect on the accuracy of dust forecasting. Some studies have tried to improve the representation of dust emissions using data assimilation techniques (e.g., Yumimoto & Takemura, 2015; Yumimoto et al., 2008). A more comprehensive assimilation is another of the challenges to be considered (Zhang et al., 2014). Ground-based observations (e.g., PM_{10} observations) remain too sparse to capture the full characteristics of dust storms. Remote sensing observation (e.g., satellite-derived aerosol optical thickness (AOT)) sometimes fails to capture dust storms under cloudy conditions. A comprehensive assimilation, in which complementary data from various observational platforms are incorporated, will lead to better dust forecasting. The quality assurance and quality control of observational data are also important regarding assimilation performance (Yu et al., 2004; Zhang & Reid, 2006). Assimilations with observations that include large errors or biases could result in the degradation of the dust forecasts.

In the present study, the work of Sekiyama et al. (2010) was extended to passive satellite imagery data and a data assimilation experiment was performed using MASINGAR for a severe dust storm that occurred on May 10–13, 2011. In the experiment, satellite-derived AOT data were assimilated to improve the initial states for the forecasts of the dust storm. The performance was evaluated by comparison of the forecast results, both with and without the assimilation, with independent in situ observations of PM_{10} from China, Korea, and Japan, as well as vertical dust profiles measured using a ground-based lidar network.

Methods

The aerosol data assimilation system consisted of a data assimilation method, aerosol transport model, and observational data. Independent observational data, which were not used in the assimilation, were used for the validations.

Data assimilation

The assimilation method employed the local ensemble transform Kalman filter (LETKF; Hunt, Kostelich, & Szunyogh, 2007). The LETKF solves an analysis state in the ensemble mean, instead of in each perturbed ensemble member, as follows:

$$\overline{\mathbf{x}^{\mathrm{a}}} = \overline{\mathbf{x}^{\mathrm{f}}} + \mathbf{K}(\mathbf{y}^{\mathrm{o}} - \overline{\mathrm{H}\mathbf{x}^{\mathrm{f}}}), \tag{1}$$

where $\mathbf{x}$ is the model state vector (e.g., dust concentration) with N dimensions and $\mathbf{y}$ is the observational vector with r dimensions. Superscripts f and a denote forecast (a priori) and analysis (a posteriori), respectively. The over bar represents the ensemble mean. H is the observational operator that converts the model state vector into the observational vector. $\mathbf{K}$ is the Kalman gain, given by

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

where $\mathbf{P}^{\mathrm{f}}$ is the forecast error covariance, $\mathbf{R}$ is the observational error covariance, and $\mathbf{H}$ is the linearized observational operator. The ensemble means and their spread are defined by

$$\overline{\mathbf{x}^{\mathrm{f}}} = \frac{1}{n}\sum_{i}^{n}\mathbf{x}_i^{\mathrm{f}}; \quad \delta\mathbf{x}_i^{\mathrm{f}} = \mathbf{x}_i^{\mathrm{f}} - \overline{\mathbf{x}^{\mathrm{f}}}; \quad \delta\mathbf{X}^{\mathrm{f}} = \left[\delta\mathbf{x}_1^{\mathrm{f}}\left|\delta\mathbf{x}_2^{\mathrm{f}}\right|\ldots\left|\delta\mathbf{x}_n^{\mathrm{f}}\right.\right], \tag{3}$$

$$\overline{\mathrm{H}\mathbf{x}^{\mathrm{f}}} = \overline{\mathbf{y}^{\mathrm{f}}} = \frac{1}{n}\sum_{i}^{n}\mathrm{H}(\mathbf{x}_i^{\mathrm{f}}); \quad \delta\mathbf{y}_i^{\mathrm{f}} = \mathbf{y}_i^{\mathrm{f}} - \overline{\mathbf{y}^{\mathrm{f}}};$$

$$\delta\mathbf{Y}^{\mathrm{f}} = \left[\delta\mathbf{y}_1^{\mathrm{f}}\left|\delta\mathbf{y}_2^{\mathrm{f}}\right|\ldots\left|\delta\mathbf{y}_n^{\mathrm{f}}\right.\right], \tag{4}$$

where i and n represent the ensemble member and size, respectively. In these equations, $\delta\mathbf{X}^{\mathrm{f}}$ is the forecast ensemble spread matrix (with $N \times n$ dimensions) and $\delta\mathbf{Y}^{\mathrm{f}}$ is the forecast ensemble spread in the observational space (with $r \times n$ dimensions). The forecast error covariance $\mathbf{P}^{\mathrm{f}}$ is represented by the forecast ensemble spread as

$$\mathbf{P}^{\mathrm{f}} = \delta\mathbf{X}^{\mathrm{f}}\left(\delta\mathbf{X}^{\mathrm{f}}\right)^{\mathrm{T}}. \tag{5}$$

One important characteristic of the LETKF is its localization technique, in which the analysis calculation is executed independently in divided local regions. This both reduces spurious error covariance with distance that can arise from sampling errors due to the limited ensemble size (Miyoshi & Yamane, 2007) and enables the use of parallel processing to reduce computational cost. Applications of the LETKF to aerosol and chemical transport models have been described by Sekiyama et al. (2010), Yumimoto and Takemura (2011), Miyazaki et al. (2012), and Yumimoto (2013).