Improved Dust Forecast by Assimilating MODIS IR-Based Nighttime AOT in the ADAM2 Model

Sang-Sam Lee1, Eun-Hee Lee2, Byung-Ju Sohn3, Hee Choon Lee4, Jeong Hoon Cho1, and Sang-Boom Ryoo1

1National Institute of Meteorological Sciences, Jeju, Korea
2Korea Institute of Atmospheric Prediction Systems, Seoul, Korea
3Seoul National University, Seoul, Korea

Abstract

A data assimilation (DA) system employing day- and nighttime aerosol optical thickness (AOT) was developed for the Asian Dust Aerosol Model 2 (ADAM2), using the optimal interpolation (OI) method. The DA system assimilated nighttime AOT for dust retrieved from MODIS infrared (IR) measurements with an artificial neural network (ANN) approach. An Asian dust case that occurred during 14–18 March 2009 was simulated using ADAM2. To examine the impact of the inclusion of nighttime AOT on forecasts of the data assimilation system, experiments were performed with different assimilation cycles (i.e., DA1: 24-hour cycle with daytime MODIS AOT only, DA2: 12-hour cycle with additional nighttime AOT). A control simulation was also performed without data assimilation (CTL). Forecasts were assessed using MODIS-derived AOT distributions as well as ground-based skyradiometer, PM₁₀, and lidar observations. The model-estimated vertical distribution of the dust extinction coefficient was also compared with lidar measurements. Both experiments (DA1, DA2) were found to have improved forecasting, but DA2 outperformed DA1. Results suggest that the ANN-based nighttime AOT contributes more positively to the forecasting through better temporal coverage for data assimilation.


1. Introduction

Mineral dust is one of the key aerosols directly and indirectly affecting the radiation budget of the Earth (Stocker et al. 2013). In the East Asian region, Asian dust generated in the Chinese and Mongolian deserts and arid regions develops into severe episodes, creating serious health and socio-economic problems. In the early 2000s, judging from the increasing frequency of such episodes in not only the source region (Inner Mongolia and northeastern China) but also in downwind regions, including Korea and Japan (Kurosaki and Mikami 2003; Tian et al. 2007; Kim 2008; Lee and Sohn 2011), this situation appeared to be worsening. However, in recent years, it is reported that the frequency of dust storms in China is decreasing (Li et al. 2015). These previous studies clearly showed that the large interannual variability of dust occurrence in the East Asian region (Hsu et al. 2012). Thus, it is important to understand the outbreak, transport, and deposition mechanism of dust aerosol. Further, knowledge about dust emission and transport modeling plays a pivotal role in understanding the recent large variability in Asian dust frequency and intensity.

Since the introduction of the Navy Aerosol Analysis and Prediction System (NAAPS)—the first operational aerosol model developed by the U.S. Navy in 1999—operational dust forecasts are now available at many meteorological agencies (UNEP, WMO, UNCCD 2016). A considerable number of studies have been conducted on dust modeling and then applied to the Asian region (e.g., Wang et al. 2000; Park and In 2003; Gong et al. 2003; Liu et al. 2003; Uno et al. 2003). These models have reproduced many important observational data and retrieved valuable information to elucidate the characteristics of the Asian dust phenomenon. However, according to the results of the recent Dust Model Intercomparison Project (DMIP), calculated amounts of dust emissions have differed even by a factor of three. Such disagreements seem to largely stem from the lack of observations of dust emission over the Mongolia and Inner Mongolia region (Uno et al. 2006).

Satellite remote sensed data will certainly provide a strong back-up for weak points of observation and play an important role in improving model forecasting capabilities for the East Asian region. Satellite observations covering extensive geographical areas have been so far used to monitor the transport of Asian dust. However, a more important application may be in the area of dust forecasting through the use of satellite data. In other words, higher temporal resolutions are essential for better data assimilation. Aerosol retrievals based on visible measurements such as MODIS estimates (Remer et al. 2005) provide a limited temporal coverage only during the daytime. Aerosol information at nighttime, or at the dawn and sunset is not available, leaving behind a huge temporal gap in the daily temporal coverage of data. Thus, the satellite data are required in addition to improved spatial coverage. Lee and Sohn (2012) developed an artificial neural network (ANN) approach for more frequent temporal acquisition of AOT by retrieving nighttime AOT using MODIS infrared (IR) brightness temperatures. In this study, we attempted to examine the possibility of applying the retrieval results of Lee and Sohn (2012) to improve the dust forecasting performance of a model. Assimilation results are validated through the comparison of the AOT simulations with AOT observations from remotely sensed data by MODIS, ground-based skyradiometer, PM₁₀, and lidar.

2. Model description

2.1 Meteorological model

The meteorological field data used in this study were obtained from the operational meteorological model outputs of the Regional Data Assimilation and Prediction System (RDAPS) of the Korea Meteorological Administration (KMA). These data are based on the MM5 version 3 that uses the x, y, and σ coordinates with a horizontal resolution of 30 km and 33 vertical layers up to the 50 hPa level. Since dusts are emitted and transported from the surface, only 25 vertical layers from the surface were used in this study.

Corresponding author: Hee Choon Lee, National Institute of Meteorological Sciences, 33 Seohobuk-ro, Seogwipo-si, Jeju-do, Korea. E-mail: lee.heechoon@korea.kr. ©2017, the Meteorological Society of Japan.
The RDAPS employs non-hydrostatic primitive physical equations of momentum, thermodynamics, and moisture with physical processes including the Kain-Fritsch scheme for convective parameterization, the mixed-phase scheme for a moisture explicit scheme, the nonlocal boundary layer scheme for the planetary boundary layer processes, and the cloud-cooling scheme for radiation.

2.2 Asian Dust Aerosol Model 2 (ADAM2)

The Asian Dust Aerosol Model 2 (ADAM2), which was developed for forecasting the evolution of Asian dust over East Asia (Park and In 2003; Park and Lee 2004; Park et al. 2010), was used in this study. ADAM2 is an Eulerian dust transport model that includes physical processes such as three-dimensional advection, diffusion, dry and wet deposition as well as dust emission from the source regions. Dust emission is parameterized on the basis of a statistical method to describe dust source regions and meteorological threshold conditions. For this purpose, the World Meteorological Organization’s 3-hourly synoptic reporting data for seven years (1996–2002) for the source region was used (Park and In 2003). The source regions of Asian dust are classified into four soil types (i.e., gobi, sand, loess, and mixed soils).

Monthly thresholds for meteorological conditions of surface wind speed, relative humidity, precipitation, and ground temperature determine the dust outbreak, depending on the soil type. Dust emission flux under satisfactory conditions is proportional to the fourth power of the friction velocity with the reduction factor (Ri) determined by the Normalized Difference Vegetation Index (NDVI) of the source region (Park et al. 2010). The ADAM2 model uses 11 size bins with the same logarithm intervals for particles of 0.1–37 μm in radius. The suspended particle size distribution is parameterized using the log-normal distributions of soil particle-size distribution bins in the source regions based on the concept of the minimally and fully dispersed particle-size distribution (Park and Lee 2004). A detailed description of the ADAM2 model can be found in Park et al. (2010).

3. Methodology

3.1 Artificial Neural Network (ANN) model

The ANN approach is a statistical and mathematical method and is used for solving problems on various Earth Science issues. Recently, ANN has been commonly used in the quantification of dust signals from space-borne measurement (e.g. Lee and Sohn 2012; Han and Sohn 2013; Wong et al. 2015; Xiao et al. 2015). In this study, a Multi-Layer Perceptron (MLP) ANN model with a backpropagation algorithm was applied. The ANN model consists of three layers: an input layer, a hidden layer, and an output layer. Following the Lee and Sohn (2012) scheme, the ANN model is composed of 17 types of input data, such as, nine MODIS brightness temperatures, six surface emissivities, relative airmass from the surface to the sensor, and topography. For the given inputs, AOT at 550 nm retrieved from MODIS is used for the target output layer. More detailed explanations of the architecture and training procedure of the ANN model are described in Lee and Sohn (2012).

3.2 Optimal interpolation

Optimal interpolation (OI) has been commonly applied for data assimilation in dust forecasting (Collins et al. 2001; Adhikary et al. 2008; Park et al. 2011). We implemented an OI technique similar to the methodology used for assimilating Indian Ocean Experiment (INDOEX) aerosol products in the Model of Atmospheric Transport and Chemistry (MATCH) model run (Collins et al. 2001). The assimilated AOT products by the OI are defined as follows:

\[ \tau^i_m = \tau_m + K (\tau_m - H \tau_m) \]

where \( \tau_m \) and \( \tau_m^i \) are the MODIS-retrieved and ADAM2-simulated AOT, respectively. \( H \) denotes the linear operator for interpolation from the model grid to the location of the observations, and \( K \) is the Kalman gain matrix (or Kalman filter). Assuming that the errors have a Gaussian distribution and that the errors in the model and observed data are not correlated to each other, the matrix \( K \) is defined as follows:

\[ K = BH (HBH^T + O)^{-1} \]

where \( B \) and \( O \) are the error covariance matrices of the background and the observation fields, respectively, which are defined as

\[ B = \begin{bmatrix} \frac{d}{2 \tau_{\text{ref}}} & \frac{d}{2 \tau_{\text{ref}}} \\ \frac{d}{2 \tau_{\text{ref}}} & \frac{d}{2 \tau_{\text{ref}}} \end{bmatrix} \]

\[ O = \begin{bmatrix} (f \tau_m + \epsilon) \times 2 & \epsilon \times 2 \\ \epsilon \times 2 & \epsilon \times 2 \end{bmatrix} \]

where \( f_m \) and \( \epsilon_m \) are the MODIS-retrieved AOT and the satellite error coefficient, respectively. A detailed description of the ADAM2 model can be found in Park et al. (2010).

3.3 Experimental design

We simulated the Asian dust case for the period of 14–18 March 2009 using the ADAM2 model. A severe dust storm, possibly associated with a strong surface pressure gradient there (not shown), was reported over southern Mongolia during the daytime on 14 March. At the same time, a low-pressure system moved through the Loess plateau, Korean peninsula, and Japan. We believe this case is relevant for showing the impact of data assimilation on the forecasting ability of the model because the storm originated from the Gobi Desert area, where data availability is low.

In order to demonstrate the impact of data assimilation on dust forecasting, one control simulation was performed without data assimilation (referred to as CTL experiment). At the same time two experiments were performed with two different assimilation conditions. First, the OI data assimilation system was applied to the ADAM2 simulation at every 00 UTC in the experiment period with MODIS/Terra visible-based AOTs, in order to examine the effect of 24-hourly data assimilation with daytime AOT only (referred to as DA1 experiment). In the second assimilation experiment, both day- and nighttime AOT retrievals were assimilated to the simulation at every 00 and 12 UTC in the forecasting period with MODIS/Terra AOT during the daytime and ANN AOT during the nighttime, respectively (referred to as DA2 experiment).

The three-dimensional mass concentration fields of each size bin were obtained from the ADAM2 simulation. Then, dust AOT was calculated theoretically by integrating the aerosol extinction efficiency \( Q_{\text{ext}}(\lambda) \) and number size distribution \( N(\lambda, \tau) \) with respect to particle radius \( \tau \) and altitude \( z \), as shown in Eq. (5).

\[ AO T_\lambda = \pi \int_0^\infty \int_\tau^\infty Q_{\text{ext}}(\lambda, \tau) N(\tau, z) \rho \tau^2 dz d\tau \]

In Eq. (5), we assumed a spherical shape for dust aerosols and a homogeneous density of 2.6 g cm\(^{-3}\). For data assimilation, we assumed that the nighttime AOT has the same observation error field as the daytime AOT used by Collins et al (2001). Assimilated AOT fields were converted linearly to the aerosol mass concentration using vertical distribution and size distribution of the model.
4. Results and discussion

An evolutionary feature of AOT from 15 to 16 March 2009 is depicted in Fig. 1. During daytime on 15 March (Fig. 1a), even though some areas in the northeast part of China were obscured by cloud contamination, a heavy dust area is evident in the region adjacent to the Bohai Sea and the Loess plateau (Fig. 1a). The dust area rapidly moved southeast on the following day, and was located in an area extending from the Yellow Sea to the Korean Peninsula on 16 March; the band-shaped area in Fig. 1c where AOTs are greater than 1.5. During the nighttime, in between two daytimes, the retrieved nighttime dust AOTs clearly depict that the dust band shown in the daytime on 15 March is located over the Bohai Sea (Fig. 1b). From the overall moving direction and AOT magnitude, the nighttime AOT field in Fig. 1b appear to be consistent with dust features found on 15 and 16 March during daytime. More AOT composites from nighttime 16 March to daytime 19 March 2009 are presented in Supplementary Fig. 1.

Figure 2 shows simulated AOTs at 12 UTC 15 March and 00 UTC 16 March from the ADAM2 CTL, DA1, and DA2 runs. In the CTL and DA1 runs, the dust area was located in the Loess Plateau where AOT was up to 2.5. However, in the DA2 assimilation result, the dust located in that region was found to be much weaker compared to the CTL and DA1 results, demonstrating the effect of assimilating the nighttime AOT field, shown in Fig. 1b. Instead, most of the Bohai Sea was under heavy dust conditions (Fig. 2c). This nighttime AOT field impacted surface PM$_{10}$ field directly in DA2 (see Supplementary Figs. 2c and 2f). After 12 hours (00 UTC 16 March), high AOT values were observed over the Yellow Sea and the east of the Korean peninsula in DA1 and DA2 (Figs. 2e and 2f), consistent with the MODIS-derived AOT distribution (Fig. 1c). In Fig. 2d, however, the CTL result shows underestimated signatures over the east of the Korean peninsula compared with the MODIS/Terra AOT (Fig. 1c). Five-hour forecasts of AOT field (05 UTC 16 March) that started from 00 UTC 16 March are shown in Fig. 3, along with MODIS/Aqua AOTs. Because Aqua satellite’s overpass time over the Korean peninsula was around 05 UTC (0350, 0530 UTC, respectively) on that day, simulation results at 05 UTC 16 March were compared with one another.

To compare assimilation results with ground-based AOT observations, skyradiometer data measured at four sites (Seoul, Yongin, Gongju, and Gosan) of the KSNET (Korean Skyradiometer NETwork) were also analyzed. Ground-based skyradiometer AOT retrievals are available only at daytime under a condition without clouds. All KSNET data used in this study were cloud-screened by using the method developed by Song et al. (2014). The comparison results for the 4 sites are given in Fig. 4 (left panel). On 15 March, AOTs observed at Seoul, Yongin, and Gongju sites rapidly increased, leaving a time lag of about a half day, compared with the CTL AOT. Nevertheless, DA1 and DA2 results show a tendency of AOT increase earlier than CTL, reducing the time lag behind the observation. In contrast, all simulated AOTs at Gosan site were well consistent with observed AOTs on 16 March. AOT observations on 16 March at Gongju site were found to be higher than that in all simulations, but DA2 results appeared to be slightly better than other simulations. Simulations on 17 March indicate that assimilation results of both DA1 and DA2 were better than the CTL, showing better agreement with observations. Furthermore, Fig. 4 (right panel) shows PM$_{10}$ comparison results for 2 sites (Baengnyeongdo and Seoul). Surface PM$_{10}$ appear to be much reduced in DA1 and DA2 rather compared to CTL for both sites. Including the 2 sites, results of surface PM$_{10}$ at eight sites in China (5 sites) and Korea (3 sites) were used for statistical analysis (Table 1). Generally, ADAM2 with data assimilation showed better performance in terms of mean bias and root mean square error (RMSE) of PM$_{10}$ simulation. Although the lowest mean bias and RMSE results vary site by site, the dust forecast performance was found to be quite improved in DA2 compared to CTL.

The observed vertical distribution of dust aerosols was com-
per compared with model-simulated results (Fig. 5). For this purpose, aerosol vertical distribution of the Asian dust and Aerosol Lidar Observation Network (AD-Net) data coordinated by the National Institute for Environmental Studies, Japan (NIES) was used. As discussed in Sugimoto et al. (2013), in this case, dust was transported through the elevated layer by convection in the mixing layer. There are limitations to direct comparisons with lidar observations because of cloud and precipitation. Nevertheless, some clear improvements could be observed in assimilated DA1 and DA2 results, compared to CTL. In Fig. 5a, lidar observations indicate that a dust layer of high optical thickness was located at around 1 km height on 16 March. This layer appears to be excessively overestimated in the CTL run. In contrast, DA1 and DA2 results show slightly weakened dust extinction coefficients, which are more agreeable considering skyradiometer data (see Fig. 4). On 17 and 18 March, however, lidar observations could not be made because of cloud contamination. For the same period, ADAM2 (CTL, DA1 and DA2) produced an elevated dust layer at 2−4 km. In particular, DA2 showed a strong extinction coefficient in the layer. Although it is difficult to quantitatively verify the layer over the Korean peninsula, high AOT areas over the Yellow Sea at daytime on 17 and 18 March could be captured by MODIS (Supplementary Fig. 1). These MODIS AOT measurements suggest that the cloud over the Korean peninsula contains aerosol loading on 17 and 18 March. In summary, these comparisons with MODIS/Aqua retrieved AOTs, ground-based skyradiometer measurements of AOT, and lidar observations show that the addition of nighttime AOT field to the MODIS daytime AOTs gave better dust forecasting results than without assimilation or assimilation of only daytime AOT.

5. Conclusions

In this study, we demonstrated the potential of nighttime AOT in improving dust forecasting. We assimilated day- and nighttime AOTs obtained for a major dust storm event that occurred on 14–18 March 2009 in the data assimilation system of ADAM2.
Fig. 3. (a) Daytime AOT retrieval from MODIS/Aqua on 16 March 2009 and dust AOT at 05 UTC 16 March 2009 simulated by ADAM2 using (b) CTL, (c) DA1, (d) DA2. These simulation results are 5 hours-forecasting AOTs from at 00 UTC 16 March 2009.

Fig. 4. (Left panel) Time series of dust AOTs simulated by ADAM2 in CTL (grey line), DA1 (blue line), and DA2 (red line) at Seoul, Yongin, Gongju and Gosan sites from 15 to 17 March 2009. CTL, DA1, and DA2 results are from 0–12 hour forecast data. Ground-based AOT observation results for each site are also given by dots. (Right upper panel) Time series of PM$_{10}$s observed (black line) and simulated by ADAM2 in CTL (grey), DA1 (blue), and DA2 (red) at Bangnyeongdo and Seoul sites. (Right lower panel) The locations of the five sites are provided.
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**Table 1.** Observed and modeled averages of PM$_{10}$ during 72 hours from 00 UTC 15 March to 00 UTC 18 March 2009, and mean bias and root mean square error (RMSE) between the observed and the modeled PM$_{10}$ in CTL, DA1, and DA2. 0−12 hour forecasts are used for the calculation.

<table>
<thead>
<tr>
<th>Station</th>
<th>Averaged PM$_{10}$ (Obs.)</th>
<th>Averaged PM$_{10}$ (Model)</th>
<th>Mean Bias (Model − Obs.)</th>
<th>RMSE</th>
</tr>
</thead>
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<tr>
<td></td>
<td>CTL</td>
<td>DA1</td>
<td>DA2</td>
<td>CTL</td>
</tr>
<tr>
<td>Erenhot</td>
<td>152.26</td>
<td>479.07</td>
<td>481.22</td>
<td>428.18</td>
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<tr>
<td>Jurhe</td>
<td>287.82</td>
<td>423.38</td>
<td>411.88</td>
<td>363.31</td>
</tr>
<tr>
<td>Dongsheng</td>
<td>311.44</td>
<td>665.33</td>
<td>667.82</td>
<td>658.82</td>
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<tr>
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<td>575.89</td>
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<td>380.60</td>
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<td>335.03</td>
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<tr>
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<tr>
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<td>291.53</td>
<td>271.19</td>
<td>289.65</td>
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</table>

*Bold indicates the lowest Mean Bias and RMSE among CTL, DA1, and DA2.

**Fig. 5.** Time-height cross section of dust extinction coefficient at Seoul from 15 to 19 March 2009, (a) observed with lidar (532 nm), and simulated by ADAM2 in (b) CTL, (c) DA1, and (d) DA2, respectively.

**References**


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