Nighttime AOT Retrieval for Asian Dusts from MODIS IR Measurements: An Artificial Neural Network Approach

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Abstract

In order to estimate MODIS-equivalent aerosol optical thicknesses (AOTs) for dust particles during the nighttime over East Asia, an Artificial Neural Network (ANN) model approach was used to combine MODIS-measured infrared (IR) brightness temperatures (BTs) and visible (VIS) AOTs. For training the ANN model, IR BTs were used together with surface type and geometrical information as inputs to predict MODIS-derived AOTs as target data during the daytime when VIS-based AOTs are available. The training was done exclusively over dust-laid pixels during the spring (March–May) of 2006 over the East Asian domain (20°N–55°N, 90°E–145°E).

It should be noted that the obtained daytime AOTs from the ANN model are in good agreement with MODIS-derived AOTs, with a correlation coefficient of 0.77 over the analysis domain. Although a weaker correlation is found during the nighttime when derived AOTs are compared against AOTs from CALIPSO, the case study indicates that the developed ANN method appears to effectively depict both the evolutionary features and intensity of the Asian dust plume during the nighttime. Results further indicate that nighttime VIS-like AOTs can be readily used for monitoring dust movement and its intensity during the nighttime, filling the gap between consecutive daytime AOT distributions.

1. Introduction

Asian dust plumes, originating in the Chinese and Mongolian desert and arid regions, significantly perturb the atmospheric radiation budget and create serious health and social problems over adjacent East Asian countries. In addition, the ramifications are not con-

fined to East Asia; it is in reality a global problem, as demonstrated in satellite remote-sensing measurements that show Asian dust being transported across the Pacific Ocean to North America (Husar et al. 2001; Eguchi et al. 2009; Yumimoto et al. 2010). Moreover, in recent decades, the frequency of the dust phenomenon over Korea and Japan has increased, likely associated with an expansion of arid areas, in particular over eastern Mongolia (Lee and Sohn 2011; Park and Sohn 2010). By contrast, dust storm occurrences over Chinese dust source regions have been trending downwards (Wang et al. 2008). Thus, accurate monitoring of the distribution and transport of Asian dust plumes are essential for understanding its implications of on climate changes and

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reducing the negative social and economic impacts.

Satellite observations covering extensive geographical areas have been used to monitor the transporting features of Asian dust (e.g., Kaufman et al. 2002). Aerosol retrievals based on visible (VIS) measurements, such as successful MODIS estimates (Remer et al. 2005), provide accurate aerosol intensities but with a limited temporal coverage, demanding more frequent measurements for better monitoring. For frequent temporal coverage, nighttime observation is much needed. However, with no VIS light available at night, the retrieval should rely on passive IR measurements or active light sources.

There have been some successes in detecting dust from remotely sensed IR measurements (Ackerman 1997; Sokolik 2002; Pierangelo et al. 2004; Li et al. 2007). For instance, the Brightness Temperature Difference (BTD) method in thermal split window channels has successfully demonstrated that dust aerosols have distinct signals relative to other aerosols and/or hydrometeors (Ackerman 1997; Legrand et al. 2001; Darmenov and Sokolik 2005; Brindley and Russell 2006; Merchant et al. 2006). However, for improved dust monitoring, physical parameters, such as aerosol optical thickness (AOT) which provides a qualitative measure of dust aerosol intensity, would likely be more beneficial, and retrieval of nighttime VIS-like AOTs should be possible. Recent studies have demonstrated that high spectral resolution infrared sounders (e.g., AIRS and IASI) are able to retrieve dust altitude and IR optical depth (Pierangelo et al. 2004; Peyridieu et al. 2010; Yao et al. 2011). In other words, IR-based AOTs can be converted into corresponding VIS-based AOTs if the spectral dependence of dust-influenced extinction efficiencies is known. Indeed, spectrally varying extinction efficiencies are readily calculable from the Mie calculation for the given refractive index and assumed size distribution.

In this study, instead of explicitly looking for a possible relationship between VIS-based AOT and IR-based AOT, we implicitly relate IR brightness temperatures (BTs) to MODIS AOTs through an ANN approach. Then, the developed method for converting IR BTs to AOTs is applied to the MODIS IR BTs measured at night to estimate nighttime AOTs carrying qualities comparable to those of MODIS VIS AOT retrievals. By enhancing the temporal coverage of the dust as well as quality of dust intensity during the nighttime, the developed method will provide a tool for better monitoring evolutionary features of the dust aerosols.

2. Methodology and datasets

2.1 Artificial Neural Network (ANN) model

In a non-scattering atmosphere, the upward radiance (I_λ) at the top of the atmosphere is influenced by surface emissivity (ϵ_λ); surface temperature (T_s); relative airmass ($m_r = 1/\mu$; $\mu = \cos \theta$, where θ is the sensor zenith angle); and the optical thickness (τ) from the surface to the top of the atmosphere (TOA), i.e.:

$$I_\lambda = \epsilon_\lambda B_\lambda(T_s) e^{-\tau_s/\mu} + \int_0^{\tau_s} B_\lambda[T(\tau')] e^{-\tau'/\mu} \frac{d\tau'}{\mu} \quad (1)$$

And the optical thickness is defined by

$$\tau = \int_0^z k_\lambda(z') \rho(z') dz' \quad (2)$$

where k_λ ($\text{cm}^2 \text{ g}^{-1}$) and ρ are absorption coefficient and density of the absorbing matter. Over the window spectral region, the total optical thickness (τ_s) can be treated as dust-only-influenced optical thickness for the dust event, which can be interpreted as a quantity nonlinearly linked to other factors such as temperature profile, moisture profile, surface temperature, and surface emissivity.

Because of the high complexity inherent in physically determining the AOT from IR BT measurements as shown in Eqs. (1) and (2), there may not be a general way to link IR BTs to VIS-based AOTs. However, in this study, we simplify the problem by only focusing on the dust under the assumption that dust aerosols emitted from arid regions of China and Mongolia maintain similar optical properties during their movement. First, we collocate the VIS-based AOTs vs. IR BTs during the daytime. Then we use the relationship obtained from collocated VIS-based AOTs vs. IR BTs during the daytime in order to retrieve nighttime AOTs. It is straightforward to convert the VIS-based optical thickness to the corresponding IR-based value, as shown for clouds, by applying the extinction efficiency Q_{ext} , given as a function of wavelength (e.g., Ham et al. 2009; Wei et al. 2004; Yang et al. 2003; Yang et al. 2000; among many others). The same conversion method can be applied to dust aerosols, and thus there should be a relationship between VIS AOT and IR AOT. As for dust aerosols, by further assuming that IR AOT can be expressed by IR BT and associated parameters (e.g., surface emissivity and surface temperature)—as demonstrated in the recent success measuring IR AOTs from AIRS and IASI IR hyperspectral (Pierangelo et al. 2004; Peyridieu et al. 2010; Yao et al. 2011)—the implicit relationship between VIS AOT and IR BT can be expected. The expected relationship may be highly nonlinear, and thus the ANN approach is used to obtain the

Fig. 1. Architecture of the ANN showing 17 inputs (8 MODIS brightness temperatures (BTs), $BT_{11 \mu m} - BT_{12 \mu m}$ (BTD), six surface emissivities (ϵ_s), relative air mass of the sensor (m_r), and topography (z_s)), a single hidden layer with 10 neurons, and a target output— $aerosol\ optical\ thickness$ (AOT).

relationship since the ANN is well known as a mathematical tool to solve forward and inverse remote sensing problems (Krasnopolsky and Schiller 2003; Mas and Flores 2008). In this study, we use the so-called Multi-Layer Perceptron (MLP) ANN model, which allows a feed-forward network to link AOT at 550 nm with BTs in the IR bands of MODIS. The multi-layer feed-forward ANN model used in this study consists of three layers—an input layer, a hidden layer, and an output layer—which are connected by synaptic weights as shown in Fig. 1.

The ANN model has a single hidden layer with 10 neurons, and a hyperbolic tangent sigmoidal function is used in all the neurons to link their nonlinear responses to given inputs. A bias parameter is also added to both the hidden and output layers for more flexible use of the activation function. In the training procedure, a learning rate of 0.1 and a bias of 1 are provided. The weight adaptation rule considered here is a *backpropagation algorithm*, which is a steepest descent algorithm to minimize the error term (the difference between actual and expected results) (Rumelhart et al. 1986; Wilde 1995). Implementation details of the training process can be found in Brierley and Batty (1999), and a more theoretical basis in Bishop (1995).

To construct ANN, we selected all IR-based factors contributing to AOT. The ANN model is made of 17 input data, nine MODIS BTs, six surface emissivities

(ϵ_λ), relative air mass from the surface to the sensor (m_r), and topography (z_s). Table 1 summarizes the inputs used. As shown in Fig. 1 and Table 1, eight MODIS BTs are directly given to the model, while $12 \mu m$ BT is indirectly given as a part of the BTD. For the given inputs, AOT at 550 nm is the target output equivalent to the AOT retrieved from Aqua MODIS measurements. One particular channel BT is removed from the total twelve channel BTs, and the remaining eleven channel BTs are used for running the ANN model. The removal procedure is continued until all twelve possible combinations are completed, and corresponding RMSEs are calculated. Then, nine MODIS BTs over the 8.6, 11, $12 \mu m$ window bands, and over the 4.3, $15 \mu m$ CO_2 absorption band were chosen, which yielded the largest nine RMSEs. Results suggest that water vapor and ozone channel BTs are least significant for the dust retrieval using the ANN model (not shown). Nonetheless, water vapor information may be necessary, in particular for the water vapor abundance rich regions, such as the open ocean, since water vapor tends to obscure the dust signal shown in the BTD (Prata 1989a, 1989b; Ackerman 1997).

2.2 Construction of training data

MODIS measures radiances at 36 spectral bands, spanning the VIS-IR region of the spectrum (from $0.415 \mu m$ to $14.235 \mu m$), with a spatial resolution of 250

Table 1. Inputs used for the artificial neural network (ANN) model.

Inputs	Notations	Descriptions
1	$BT_{4.4 \mu m}$	Brightness temperature at $4.4 \mu m$
2	$BT_{4.5 \mu m}$	Brightness temperature at $4.5 \mu m$
3	$BT_{8.6 \mu m}$	Brightness temperature at $8.6 \mu m$
4	$BT_{11 \mu m}$	Brightness temperature at $11 \mu m$
5	$BTD (BT_{11 \mu m} - BT_{12 \mu m})$	Brightness temperature difference between 11 and $12 \mu m$
6	$BT_{13.3 \mu m}$	Brightness temperature at $13.3 \mu m$
7	$BT_{13.6 \mu m}$	Brightness temperature at $13.6 \mu m$
8	$BT_{13.9 \mu m}$	Brightness temperature at $13.9 \mu m$
9	$BT_{14.2 \mu m}$	Brightness temperature at $14.2 \mu m$
10	$8.6 \mu m$	Surface emissivity at $8.6 \mu m$
11	$11 \mu m$	Surface emissivity at $11 \mu m$
12	$12 \mu m$	Surface emissivity at $12 \mu m$
13	$4.4 \mu m$	Surface emissivity at $4.4 \mu m$
14	$4.5 \mu m$	Surface emissivity at $4.5 \mu m$
15	$13.3 \mu m$	Surface emissivity at $13.3 \mu m$
16	m_r	Relative airmass (secant of sensor zenith angle)
17	z_s	Topography

m, 500 m, and 1 km at nadir, depending on the wavelength. Its large swath of 2,330 km enables global coverage within one or two days (Salomonson et al. 1989). The ANN model contains nine MODIS BTs to implicitly represent the surface temperature by including atmospheric window bands (band 29, 31, 32) and the temperature profile by CO_2 absorption bands in the $4.3 \mu m$ region (band 24, 25) and $15 \mu m$ region (band 33, 34, 35, 36). Information on the MODIS IR bands used in this study is summarized in Table 2. The nine MODIS BTs are inverted from MODIS Level 1B calibrated radiance using the inverse of the Planck function with sensor response functions. $BTD (BT_{11 \mu m} - BT_{12 \mu m})$ is explicitly included as an input variable because it is sensitive to dust (Ackerman 1997).

Surface emissivity spectra (ϵ_λ) are obtained from the ASTER IR spectral library in conjunction with 17 International Geosphere-Biosphere Programme (IGBP) surface types. In this study we adopt the Wilber et al. (1999) method showing how nine surface types (conifer, deciduous, quartz sand, grass, seawater, black body, fine snow and ice, medium snow and ice, coarse snow and ice) in the ASTER spectral library are linked to 17 IGBP surface types. Here IGBP surface types for any given location are obtained from the MODIS MYD12_Q1 product of the IGBP Land Cover Type. This data includes the 17 classes of land cover in the IGBP global vegetation classification scheme. For each IGBP surface type, IR spectral emissivities in the ASTER library are weighted and averaged for MODIS IR spectral bands

by applying corresponding spectral response functions. Since the emissivities provided in the spectral library range from 3.5 to $14 \mu m$ emissivities, only those at MODIS bands (24, 25, 29, 31, 32, 33) were selected. Land surface topography (z_s) is also included in the inputs, and we use 1-km resolution data obtained from the average of the USGS SRTM30 gridded DEM product created with data from the NASA Shuttle Radar Topography Mission.

AOTs at 550 nm as target data of ANN are extracted from MYD04_L2 products: ‘Deep Blue Aerosol Optical Depth 550 Land’ for land, and ‘Optical Depth Land and Ocean’ for ocean (Levy et al. 2003; Hsu et al. 2004). For constructing the ANN model, all input and target data are prepared in the $0.2^\circ \times 0.2^\circ$ grid format over the East Asian domain ($20^\circ N - 55^\circ N$, $90^\circ E - 145^\circ E$). Since the East Asian dust phenomenon mostly occurs in the spring, the training data were collected from March to May 2006.

The method applies only to the dust aerosols. To determine the dust-laid pixels using IR channels, we use D^* -parameter, which is based on the spectral variability of dust emissivity at 8.6, 11 and $12 \mu m$ wavelengths (Hansell et al. 2007). The D^* -parameter is constructed with $BTD (11 \mu m - 12 \mu m)$ and $BTD (8.6 \mu m - 11 \mu m)$ as follows:

$$D^* = \exp \left[\frac{(BT_{11 \mu m} - BT_{12 \mu m}) - C}{(BT_{8.6 \mu m} - BT_{11 \mu m}) - E} \right] \quad (3)$$

Table 2. Characteristics of the MODIS IR channels used in this study.

Band	Range (μm)	T_{typical} (K)	Radiance at T_{typical} ($\text{W m}^{-2}\mu\text{m}^{-1}\text{sr}^{-1}$)	Application (this study)
24	4.433–4.498	250	0.17	BT, ε
25	4.482–4.549	275	0.59	BT, ε
29	8.400–8.700	300	9.58	BT, ε , Dust detection
31	10.780–11.280	300	9.55	BT, ε , Dust detection
32	11.770–12.270	300	8.94	BT, ε , Dust detection
33	13.185–13.485	260	4.52	BT, ε
34	13.485–13.785	250	3.76	BT
35	13.785–14.085	240	3.11	BT
36	14.085–14.385	220	2.08	BT

where parameters C and E represent the thermal offsets for BTD ($11\ \mu\text{m}$ – $12\ \mu\text{m}$) and BTD ($8.6\ \mu\text{m}$ – $11\ \mu\text{m}$), respectively. For use of the D^* -parameter, the offsets C and E in Eq. (3) were set to -0.5 and 15 , respectively (Hansell et al. 2007). The dust presence is assumed if $D^* > 1$, as shown in Hansell et al. (2007).

For training the ANN model, 208,802 pixels were collected in spring 2006 when $D^* > 1$ and MODIS AOT was available. Among these, 146,161 pixels (about 70% of the data) were randomly chosen for the calibration, and the remaining 62,641 pixels (about 30% of the data) were used for the model validation. The calibration dataset is further divided into a training data set of 104,401 pixels (50% of the data) and a testing data set of 41,760 pixels (20% of the data). The training datasets were used to train the ANN models by updating weights. The performance of the learning process was then compared using an independent testing dataset after each training-iteration, and the network with the smallest error with respect to the testing dataset was selected. The performance of the selected network should be confirmed by measuring its performance on a third independent validation dataset. Input and output data over all pixels are normalized in the range of -1 to 1 by using their minimum and maximum data. It is because of different units and ranges of input/output data, that normalization is necessary. It is also needed for the use of hyperbolic tangent sigmoid function whose range is between -1 and 1 . In addition, for the first training, the ANN model generated initial random synaptic weights ranging from -0.1 to 0.1 . Finally, the optimal synaptic weights were determined when the convergent RMSEs of training, testing, and validation were $9.908\text{E}-2$, $1.004\text{E}-1$, and $1.010\text{E}-1$, respectively.

3. Results

3.1 Evolutionary feature of 7–8 April dust event

An intense Asian dust event was observed over the East Asian region on 7–8 April 2006 (Fig. 2). A dust band was clearly observed moving rapidly from northwest to southeast, taking only one day to pass across the Korean peninsula and reach the Japanese archipelago. Figure 2a is a daytime composite AOT image from eight granules (0355, 0400, 0530, 0535, 0540, 0710, 0715, 0720 UTC on 7 April) of MYD04 products. Figure 2b is a composite image of nighttime ANN AOT constructed from six granules (1600, 1730, 1735, 1740, 1910, 1915 UTC on 7 April). Figure 2c is the same as Fig. 2a, but from 0300, 0305, 0435, 0440, 0445, 0615, and 0620 UTC on 8 April 2006.

Figure 2 provides an evolutionary feature of the dust event. During the daytime of 7 April, a heavy dust area appeared to be over Manchuria, southeast of eastern Mongolia—the exact area is obscured by cloud contamination. A second dust band that may or may not have the same origin as the one in Manchuria is also visible along about 35N parallel from China to Korea. After one day, on 8 April, the dust area located in Manchuria rapidly moved southeast and formed a dust band extending from the Shandong peninsula in China to the Korean peninsula and over to Shimane prefecture in Japan with AOTs greater than 2.0 in Japan (Fig. 2c). The retrieved nighttime dust AOT clearly suggests that the dust band shown in the daytime of 8 April indeed passed across the Korean peninsula (Fig. 2b), when the direction of movement and AOT values are considered. It shows that the intensity of AOT retrieved over the Korean peninsula declines at night, and yet a dust band with a large AOT, of around 2.0 , is still discernible.

The evolutionary feature of the dust at nighttime

Fig. 2. Time evolution of AOT composite images: (a) from MODIS in the daytime on 7 April, (b) from ANN model at nighttime on 7 April, and (c) from MODIS in the daytime on 8 April 2006.

Fig. 3. Left: Geographical locations of three PM₁₀ sites (Gwanaksan, Gwangdeoksan, and Ulleungdo) in Korea. Right: Time series of PM₁₀ measurements at Gwanaksan (solid thin line), Gwangdeoksan (solid line with dots), and Ulleungdo (solid thick line) sites on April 7–8, 2006. Vertical bars represent the Aqua overpass time in Korean local time (i.e., 0355 UTC (1255 LST) 7 April, 1735 UTC 7 April (0235 LST 8 April), and 0440 UTC (1340 LST) 8 April). The AOT values at three sites from Fig. 2 are also given on bars using the same symbols in the left panel, and scale is given on the right-hand side.

dust appears to be manifested by the time series of ground-based PM₁₀ data observed at three sites in Korea (Gwanaksan, Gwangdeoksan, and Ulleungdo) on 7–8 April, 2006 (Fig. 3). The PM₁₀ time series indicate sudden increases of surface aerosol concentrations at the northwestern South Korean sites (Gwanaksan and Gwangdeoksan) just before 00 LST 8 April and at the eastern site (Ulleungdo) after 00 LST 8 April, suggesting the arrival of the dust plume during the night of 7 April. The dust plume arrived during the night of 7 April, became stronger in on the following day (8 April), and then became weaker in during the night of 8 April in Korea.

Although the direct comparison between AOT and PM₁₀ concentration may not provide a linear relationship, Fig. 3 demonstrates that the ANN-derived AOTs depict well an evolutionary feature of the dust plume. During the Aqua passage in the daytime of 7 April, there was no AOT observation due to cloud contamination. But, the next passage at 1735 UTC 7 April (0235 LST 8 April) showed a high ANN AOT over the northwestern sites (Gwanaksan and Gwangdeoksan) of 0.79 and 1.24, respectively. And Additionally, the third passage at 0440 UTC (1340 LST) 8 April showed high AOT of 1.50, 0.79, and 1.48 over the Gwanaksan, Gwangdeoksan, and Ulleungdo sites, re-

spectively. Around 0235 LST of April 8 (the second bar), the coincidental increase of PM₁₀ and AOT at the Gwanaksan and Gwangdeoksan sites strongly suggests that the ANN-AOT distribution given in Fig. 2b represents the an AOT distribution that might be observable if a VIS light source were available.

3.2 Model validation

As shown in the case study of Fig. 2, it must be beneficial to use the derived nighttime AOTs for the dust monitoring because the pattern as well as intensity of nighttime dust bands are captured well by the developed ANN method. Since such assessment is a qualitative measure, in this section, quantitative validation efforts are given by comparing first ANN retrievals with MODIS AOT data from spring 2007, independent of the training dataset. Figure 4 illustrates a dust event that occurred in East Asia at 0405 UTC (1305 LST in Korea) on 1 April 2007. The MODIS AOT product and ANN retrieval are compared to assess the performance of the ANN method depicting the spatial distribution. Despite cloud contamination, the Aqua/MODIS AOT product (Fig. 4a) and RGB image (Fig. 4c) clearly captured a heavy dust band passing over the Korean peninsula and spreading to the Hokkaido island of Japan. Heavy dust aerosol, with an optical thickness of over

Fig. 4. (a) MODIS (Aqua) retrieved AOT, (b) ANN retrieved AOT, (c) MODIS true color images of dust storm outbreak on the Korean peninsula, and (d) scatter plot between MODIS AOT and ANN AOT at 0405 UTC on 1 April 2007. The brightness temperature at $11\ \mu\text{m}$ is added on the background of (a) and (b) to show the cloud distribution. The red coastline in (c) delineates the Korean peninsula. The solid line in (d) is the one-to-one matching line between the MODIS and ANN AOT. The dashed and chain-dashed lines represent 20% and 30% difference, respectively.

4.0, is observed in the area off the east coast of Korea (Fig. 4a). This feature is also found in the ANN model result (Fig. 4b). When compared with the RGB image (Fig. 4c), high ANN AOT (in Fig. 4b) covers a wider area but the spatial distribution has a similar pat-

tern. Contrary to the high AOT case, the southern coast of Japan, showing a low AOT, is excluded by the D^* -parameter in Fig. 4b, suggesting that the aerosols over those regions may not be dust related. Figure 4d shows a scatter plot between simultaneously retrieved instant-

Fig. 5. Same as Fig. 4, except for the dust plume on the eastern part of China at 0615 UTC on 4 April 2007.

neous MODIS (Fig. 4a) and ANN (Fig. 4b) AOT. Also shown are the slope and intercept, the linear correlation coefficient R , and the number of data points (N). The regression equation, with a positive offset (0.89) and slope lower than unity (0.68), suggests overestimation for relatively low AOT and underestimation for high AOT. The comparison shows that the ANN AOTs gener-

ally lie within 30% of the MODIS AOTs. The numbers of pixels within a 20% and 30% difference in Fig. 4d are 61 and 78, respectively. As a result, only 28 pixels out of the total 106 pixels lie outside the 30% difference. The ANN AOT also delineates a strong linear relationship with the MODIS AOT with a correlation coefficient of 0.86. Although the MODIS ocean algorithm does not

Table 3. Number of matched pixels (N), regression results (slope, intercept), root mean square error (RMSE), and correlation coefficient (R) between MODIS and ANN AOT for each IGBP type during spring (March–May) 2007.

IGBP Type	N	Slope	Intercept	RMSE	Mean Bias (ANN-MODIS)	R
1. Evergreen Needleleaf Forest	11	-0.10	0.54	0.28	0.19	-0.20
2. Evergreen Broadleaf Forest	0	—	—	—	—	—
3. Deciduous Needleleaf Forest	0	—	—	—	—	—
4. Deciduous Broadleaf Forest	17	0.14	0.61	0.41	0.19	0.16
5. Mixed Forest	654	0.35	0.44	0.36	0.03	0.65
6. Closed Shrublands	16	0.02	0.49	0.19	-0.09	0.05
7. Open Shrublands	11,402	0.78	0.06	0.26	0.00	0.70
8. Woody Savannas	22	0.66	0.34	0.27	0.17	0.74
9. Savannas	19	0.23	0.33	0.38	-0.10	0.62
10. Grasslands	29,637	0.67	0.07	0.23	-0.01	0.77
11. Permanent Wetlands	0	—	—	—	—	—
12. Croplands	7,600	0.64	0.27	0.50	0.00	0.70
13. Urban	139	0.70	0.19	0.43	-0.05	0.72
14. Cropland/Mosaic	14	0.36	0.29	0.50	-0.20	0.77
15. Snow and Ice	0	—	—	—	—	—
16. Barren	105,525	0.56	0.13	0.29	0.00	0.75
17. Water Bodies	866	0.67	0.48	0.82	-0.11	0.82
Mean	(155,922) ^a	0.63	0.12	0.30	0.00	0.77

a: The value represents the total number.

Fig. 6. Histogram of the AOT at 550 nm between MODIS retrievals and ANN model results for all IGBP surface types for the March–May 2007 period.

perform well with heavy dust due to its non-sphericity (Levy et al. 2003), from the point of view of ANN performance, it is worthwhile to note the consistency with MODIS AOTs.

Beside the ocean comparison shown in Fig. 4, a land case is examined separately (Fig. 5). This illustrates a dust event that occurred in the eastern part of China at 0615 UTC (1515 LST in Korea) on 4 April 2007. The spatial distribution of the ANN AOT (Fig. 5b) is in good agreement with the MODIS AOT product (Fig. 5a). Similar to the ocean case, the ANN AOTs appeared to be overestimated for the small MODIS AOT region while underestimated for the large MODIS AOT region, as shown in the scatter plot of instantaneous AOTs (Fig. 5d). Compared with Fig. 4d, the statistics show slightly better performance (0.73 of slope, 0.13 of intercept, and 0.87 of correlation coefficient).

Comparison is also made for the entire spring of 2007. Table 3 summarizes the number of matched pixels (N), regression results (slope, intercept), root mean square error (RMSE), and correlation coefficient (R) between the MODIS and ANN AOTs for each IGBP type. A total of 155,922 pixels were identified as dust by the D^* -parameter. The slope, intercept, and correlation coefficient obtained from the linear regression are 0.63,

Fig. 7. IGBP surface types and histograms of the AOT at 550 nm between MODIS retrievals and ANN model results for six major IGBP surface types for the March–May 2007 period.

Fig. 8. Scatter plots between (a) MODIS AOT at 550 nm and CALIPSO AOT at 532 nm, and (b) between ANN AOT at 550 nm and CALIPSO AOT at 532 nm for the daytime.

0.12, and 0.77, respectively, indicating a general overestimation (underestimation) of AOT by the ANN method for weak (strong) dust cases.

The frequency distributions for the given MODIS and ANN AOTs in Fig. 6 indicate that most dust pixels show AOTs smaller than 1, and they are again generally overestimated by the ANN method. On the other hand, for the relatively heavier dust cases, distributions show a bi-modal pattern; i.e., one extending diagonally and the other bulging toward the lower estimate by the ANN method. Overall, the ANN method tends to underestimate the AOT when the dust loading is heavy.

In order to further examine the bimodal pattern shown in Fig. 6, we look at the frequency distributions classified by six major IGBP types, which account for more than 98% of the total pixels (see Fig. 7). Among them, the 'Barren' type, accounting for more than two thirds of the collected cases, shows clear underestimates by the ANN method, and underestimation is more evident for heavy dust cases showing MODIS AOT greater than 1.0. This underestimation is manifested by the low value of the regression slope (i.e. 0.54). A less significant underestimate is clear for the 'Grasslands' type, which covers the second largest area in the domain, with a regression slope of 0.65 and correlation coefficient of 0.77. In the 'Croplands' region, the agreement is quite

good, as shown in the intercept point of 0.06 and slope of 0.78. Unlike other land types, the bias is small in the 'Water Bodies' type, which exhibits a regression slope and correlation coefficient of 0.72 and 0.85, respectively. Since the MODIS over-ocean algorithm is known to perform better than the over-land algorithm (Tanré et al. 1999; King et al. 1999; Remer et al. 2005), the ANN-derived AOTs are also considered to be better over the ocean. It is because the ANN method depends on the quality of the training data. Overall, the results indicating that the regression statistics depend on the surface types suggest that the surface emissivity may be an important parameter influencing the performance. Specification of more accurate surface emissivity may be necessary for better results from the ANN method.

Since nighttime AOTs are not available from VIS measurements, we use CALIPSO lidar level 2 aerosol layer products for the validation of the ANN model results during the nighttime. In this validation, the horizontal resolution of the CALIPSO AOT was set to 0.2 degrees to match up with the ANN AOT. However, since the CALIPSO data are taken only along the satellite track, the 0.2 degree average implies a horizontal average along the satellite track. Cloud contamination was excluded by using only the pixels whose cloud optical thickness is zero. Before the nighttime validation,

Fig. 9. Scatter plot between ANN AOT at 550 nm and CALIPSO AOT at 532 nm for nighttime.

the daytime CALIPSO and MODIS AOTs were compared, as shown in Fig. 8a, in order to provide the basis for validation of the ANN and CALIPSO AOTs. The estimated retrieval error of MODIS aerosol products are known to be $\Delta\tau = \pm 0.03 \pm 5\%$ over the ocean and $\Delta\tau = \pm 0.05 \pm 15\%$ over the land (Remer et al. 2005). However, over the land, instead of the MODIS standard product of “dark-target” approach (Kaufman et al. 1997), we used the “Deepblue” product (Hsu et al. 2004) claimed to be in better agreement with ground-based observations (Ge et al. 2010). Meanwhile, CALIPSO AOT shows a systematic underestimation compared with MODIS AOT (Royer et al. 2010; Kacenelenbogen et al. 2011; Yumimoto et al. 2008). Furthermore, a recent comparison study indicates that differences between CALIPSO and MODIS AOTs over land are larger than those over ocean. However, the bias in AOTs between the two sensors is within the uncertainty level only on a regional-seasonal basis, even for ocean cases (Kittaka et al. 2011). And these differences are mainly due to the limitation of the CALIPSO retrieval algorithm (Kittaka et al. 2011).

The comparison between daytime MODIS AOT and CALIPSO AOT reflects the complexity of interpreting the CALIPSO-derived AOTs (Fig. 8a). Considering that comparison is made on the pixel basis and that CALIPSO AOTs are comparable to MODIS AOTs on the seasonal-regional basis (Kittaka et al. 2011), the

considerably scattered pattern with coefficient of 0.16 shown in Fig. 8a is not surprising. Nonetheless, the comparison of pixel-based ANN AOTs with CALIPSO pixels shows a somewhat similar performance (Fig. 8b), with a correlation coefficient of 0.32—but only for the dust pixels based on the use of D^* -parameter.

Nighttime comparison of ANN-based AOTs is made again with CALIPSO measurements (Fig. 9). It shows a very scattered pattern and substantial overestimate of in AOT by the ANN method during the nighttime. Although the statistics indicates that ANN AOTs and CALIPSO AOTs are not in a correlated relationship, it is notable to observe that the nighttime ANN AOT (Fig. 9) is quite similar to the daytime scattered pattern between MODIS AOT and CALIPSO AOT (Fig. 8a). However, again considering the different quantities existing between MODIS and CALIPSO-derived AOT, further research should be conducted with a longer data set to draw a firm conclusion about the performance of the ANN method to retrieve the nighttime AOTs.

4. Conclusions and discussion

Nighttime AOTs equivalent to daytime quantities derived from satellites must be useful for better depiction of dust movement and thus better dust monitoring. In this study, an IR-based ANN model was constructed and applied to the East Asian region to derive nighttime AOT. MODIS IR BTs, BT difference between split window channels (i.e. $BT_{11\ \mu m} - BT_{12\ \mu m}$), ASTER-based surface emissivities, satellite viewing angle, and topography were used as inputs to the ANN model, and were related to MODIS AOTs at 550 nm during the daytime using an ANN approach. The developed method was then applied to obtain the MODIS-equivalent nighttime AOT, which should have considerable benefits for interpreting the transport route and intensity of dust plumes.

To assess the performance of ANN model, daytime ANN-produced AOT was compared with MODIS AOT for the spring of 2007, independent from its training period (i.e., the spring of 2006). The regression result indicates that ANN-produced AOTs are statistically comparable to MODIS AOT measurements although a general underestimate is evident. The regression slope, intercept value, and correlation coefficient are 0.63, 0.12, and 0.77, respectively. Furthermore, underestimates by the ANN method and associated statistics appear to be dependent upon the surface types, suggesting that more accurate description of surface emissivities in grid scale over the entire IR spectral range may bring in better agreement. However, from the fact that IR BTs are sensitive mainly to the dusts while VIS-based AOTs are also sensitive to most aerosol species, the underes-

timate of AOTs by the IR-based ANN method in nature may not be avoidable. On the other hand, the used CALIPSO-based AOTs appeared to be insufficient for validating the ANN method during the nighttime because CALIPSO AOT has a much different quantity from MODIS AOT, and the developed ANN method was trained against MODIS measurements. However, if the dust impact on IR BTs obtained during the daytime is assumed to hold its validity during the nighttime, a similar ANN performance as that shown in the daytime can be expected to occur at night. Overall this study demonstrated that the ANN model can produce MODIS-like AOT retrievals during the nighttime from which dust monitoring can be effectively done with better information on the dust distribution and intensity.

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References

- Ackerman, S. A., 1997: Remote sensing aerosols using satellite infrared observations, *J. Geophys. Res.*, **102**, 17,069–17,079.
- Bishop, C. M., 1995: *Neural Networks for Pattern Recognition*, Oxford University Press, 504 pp.
- Brierley, P., and B. Batty, 1999: Data mining with neural networks—an applied example in understanding electricity consumption patterns, *Knowledge Discovery and Data Mining*, edit. M. A. Bramer, Institution of Electrical Engineers, 240–303.
- Brindley, H. E., and J. E. Russell, 2006: Improving GERB scene identification using SEVIRI: Infrared dust detection strategy, *Remote Sens. Environ.*, **104**, 426–446.
- Darmenov, A., and I. N. Sokolik, 2005: Identifying the regional thermal-IR radiative signature of mineral dust with MODIS, *Geophys. Res. Lett.*, **32**, L16803, doi:10.1029/2005GL023092.
- Eguchi, K., I. Uno, K. Yumimoto, T. Takemura, A. Shimizu, N. Sugimoto, and Z. Liu, 2009: Trans-Pacific dust transport: Integrated analysis of NASA/CALIPSO and a global aerosol transport model, *Atmos. Chem. Phys.*, **9**, 3137–3145, doi:10.5194/acp-9-3137-2009.
- Ge, J. M., J. Su, T. P. Ackerman, Q. Fu, J. P. Huang, and J. S. Shi, 2010: Dust aerosol optical properties retrieval and radiative forcing over northwestern China during the 2008 China-U. S. joint field experiment, *J. Geophys. Res.*, **115**, D00K12, doi:10.1029/2009JD013263.
- Ham, S.-H., B. J. Sohn, P. Yang, and B. A. Baum, 2009: Assessment of the quality of MODIS cloud products from radiance simulations. *J. Appl. Meteor. Climatol.*, **48**, 1591–1612.
- Hansell, R. A., S. C. Ou, K. N. Liou, J. K. Roskovensky, S. C. Tsay, and C. Hsu, 2007: Simultaneous detection/separation of mineral dust and cirrus clouds using MODIS thermal infrared window data, *Geophys. Res. Lett.*, **34**, L11808, doi:10.1029/2007GL029388.
- Hsu, N. C., S.-C. Tsay, M. D. King, and J. R. Herman, 2004: Aerosol properties over bright-reflecting source regions, *IEEE Trans. Geosci. Remote Sens.*, **42**, 557–569.
- Husar, R. B., D. M. Tratt, B. A. Schichtel, S. R. Falke, F. Li, D. Jaffe, et al., 2001: Asian dust events of April 1998, *J. Geophys. Res.*, **106**, 18,317–18,330.
- Kacenelenbogen, M., M. A. Vaughan, J. Redemann, R. M. Hoff, R. R. Rogers, R. A. Ferrare, P. B. Russell, C. A. Hostetler, J. W. Hair, and B. N. Holben, 2011: An accuracy assessment of the CALIOP/CALIPSO version 2/version 3 daytime aerosol extinction product based on a detailed multi-sensor, multi-platform case study, *Atmos. Chem. Phys.*, **11**, 3981–4000.
- Kaufman, Y. J., D. Tanré, L. A. Remer, E. Vermote, A. Chu, and B. N. Holben, 1997: Operational remote sensing of tropospheric aerosol over land from EOS moderate resolution imaging spectroradiometer, *J. Geophys. Res.*, **102**, 17,051–17,067.
- Kaufman, Y. J., D. Tanré, and O. Boucher, 2002: A satellite view of aerosols in the climate system, *Nature*, **419**, 215–223.
- King, M. D., Y. J. Kaufman, D. Tanré, and T. Nakajima, 1999: Remote sensing of tropospheric aerosols from space: Past, present and future, *Bull. Amer. Meteor. Soc.*, **80**, 2229–2259.
- Kittaka, C., D. M. Winker, M. A. Vaughan, A. Omar, and L. A. Remer, 2011: Intercomparison of column aerosol optical depths from CALIPSO and MODIS-Aqua. *Atmos.*

- Meas. Tech.*, **4**, 131–141.
- Krasnopolsky, V. M., and H. Schiller, 2003: Some neural network applications in environmental sciences. Part I: forward and inverse problems in geophysical remote measurements, *Neural Networks*, **16**, 321–334.
- Lee, E.-H., and B.-J. Sohn, 2011: Recent increasing trend in dust frequency over Mongolia and Inner Mongolia regions and its association with climate and surface condition change, *Atmos. Environ.*, **45**, 4611–4616, doi:10.1016/j.atmosenv.2011.05.065.
- Legrand, M., A. Plana-Fattori, and C. N'doumé, 2001: Satellite detection of dust using the IR imagery of Meteosat: 1. Infrared difference dust index, *J. Geophys. Res.*, **106**, 18,251–18,274.
- Levy, R. C., L. A. Remer, D. Tanré, Y. J. Kaufman, C. Ichoku, B. N. Holben, J. M. Livingston, P. B. Russell, and H. Maring, 2003: Evaluation of the Moderate-Resolution Imaging Spectroradiometer (MODIS) retrievals of dust aerosol over the ocean during PRIDE, *J. Geophys. Res.*, **108**, 8594, doi:10.1029/2002JD002460.
- Li, J., P. Zhang, T. J. Schmit, J. Schmets, and W. P. Menzel, 2007: Quantitative monitoring of a Saharan dust event with SEVIRI on Meteosat-8, *Int. J. Remote Sens.*, **28**, 2181–2186.
- Mas, J. F., and J. J. Flores, 2008: The application of artificial neural networks to the analysis of remotely sensed data, *Int. J. Remote Sens.*, **29**, 617–663.
- Merchant, C. J., O. Embury, P. Le Borgne, and B. Bellec, 2006: Saharan dust in nighttime thermal imagery: Detection and reduction of related biases in retrieved sea surface temperature, *Remote Sens. Environ.*, **104**, 15–30.
- Park, H.-S., and B.-J. Sohn, 2010: Recent trends in changes of vegetation over East Asia coupled with temperature and rainfall variations, *J. Geophys. Res.*, **115**, D14101, doi:10.1029/2009JD012752.
- Peyridieu, S., A. Chédin, D. Tanré, V. Capelle, C. Pierangelo, N. Lamquin, and R. Armante, 2010: Saharan dust infrared optical depth and altitude retrieved from AIRS: a focus over North Atlantic—comparison to MODIS and CALIPSO, *Atmos. Chem. Phys.*, **10**, 1953–1967.
- Pierangelo, C., A. Chédin, S. Heilliette, N. Jacquinet-Husson, and R. Armante, 2004: Dust altitude and infrared optical depth from AIRS, *Atmos. Chem. Phys.*, **4**, 1813–1822.
- Prata, A. J., 1989a: Observation of volcanic ash clouds in the 10–12 μm window using AVHRR-2 data, *Int. J. Remote Sens.*, **10**, 751–761.
- Prata, A. J., 1989b: Infrared radiative transfer calculations for volcanic ash clouds, *Geophys. Res. Lett.*, **16**, 1293–1296.
- Remer, L., Y. Kaufman, D. Tanré, S. Mattoo, D. Chu, J. Martins, et al., 2005: The MODIS aerosol algorithm, products, and validation, *J. Atmos. Sci.*, **62**, 947–973.
- Royer, P., J.-C. Raut, G. Ajello, S. Berthier, and P. Chazette, 2010: Synergy between CALIOP and MODIS instruments for aerosol monitoring: application to the Po Valley, *Atmos. Meas. Tech.*, **3**, 893–907.
- Rumelhart, D. E., J. L. McClelland, and the PDP Research Group, 1986: *Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Volume 1, Foundations*. The MIT Press, Cambridge, MA. 564 pp.
- Salomonson, V. V., W. L. Barnes, P. W. Maymon, H. E. Montgomery, and H. Ostrow, 1989: MODIS: Advanced Facility Instrument for Studies of the Earth as a System, *IEEE Trans. Geosci. Remote Sens.*, **27**, 145–153.
- Sokolik, I. N., 2002: The spectral radiative signature of wind-blown mineral dust: Implications for remote sensing in the thermal IR region, *Geophys. Res. Lett.*, **29**, 2154, doi:10.1029/2002GL015910.
- Tanré, D., L. A. Remer, Y. J. Kaufman, S. Mattoo, P. V. Hobbs, J. M. Livingston, P. B. Russell, and A. Smirnov, 1999: Retrieval of aerosol optical thickness and size distribution over ocean from the MODIS Airborne Simulator during TARFOX, *J. Geophys. Res.*, **104**, 2261–2278.
- Wang, X., J. Huang, M. Ji, and K. Higuchi, 2008: Variability of East Asia dust events and their long-term trend, *Atmos. Environ.*, **42**, 3156–3165.
- Wei, H., P. Yang, J. Li, B. A. Baum, A. Huang, S. E. Platnick, Y.-X. Hu, and L. Strow, 2004: Retrieval of semitransparent ice cloud optical thickness from Atmospheric Infrared Sounder (AIRS) measurements, *IEEE Trans. Geosci. Remote Sens.*, **42**, 2254–2267.
- Wilber, A. C., D. P. Kratz, and S. K. Gupta, 1999: Surface emissivity maps for use in satellite retrievals of long-wave radiation. NASA Technical Report. NASA/TP-1999–209362, NASA, 30 pp.
- Wilde, P. D., 1995: *Neural Network Models—An Analysis*, Springer, London, UK, 153 pp.
- Yang, P., K. N. Liou, K. Wyser, and D. Mitchell, 2000: Parameterization of the scattering and absorption properties of individual ice crystals, *J. Geophys. Res.*, **105**, 4600–4718.
- Yang, P., B. A. Baum, A. J. Heymsfield, Y. X. Hu, H.-L. Huang, S.-C. Tsay, and S. Ackerman, 2003: Single-scattering properties of droxtals, *J. Quant. Spectrosc. Radiat. Transfer*, **79–80**, 1159–1169.
- Yao, Z., J. Li, H.-J. Han, A. Huang, and B.-J. Sohn, 2011: Asian dust height and infrared optical depth retrievals from hyperspectral longwave infrared radiances, Submitted to *J. Geophys. Res.*
- Yumimoto, K., I. Uno, N. Sugimoto, A. Shimizu, Z. Liu, and D. M. Winker, 2008: Adjoint inversion modeling of Asian dust emission using lidar observations, *Atmos. Chem. Phys.*, **8**, 2869–2884.
- Yumimoto, K., K. Eguchi, I. Uno, T. Takemura, Z. Liu, A. Shimizu, N. Sugimoto, and K. Strawbridge, 2010: Summertime trans-Pacific transport of Asian dust, *Geophys. Res. Lett.*, **37**, L18815, doi:10.1029/2010GL043995.