Retrieval of the Haze Optical Thickness in North China Plain Using MODIS Data

Shenshen Li, Liangfu Chen, Xiaozhen Xiong, Jinhua Tao, Lin Su, Dong Han, and Yang Liu

Abstract—China’s industrialized regions have seen increasing occurrence of heavy haze caused by severe particle pollution. However, aerosol retrieval under these circumstances is often excluded from NASA’s Moderate Resolution Imaging Spectrometer (MODIS) aerosol products due to cloud mask and suspected high surface reflectance. An algorithm to retrieve the haze aerosol optical thickness (HAOT) is developed using MODIS data to supplement the current MODIS retrieval algorithm. This method includes 1) haze identification, 2) the generation of a surface reflectance database using MODIS data in hazy conditions, and 3) the development of haze aerosol models with four aerosol components simulated by a global 3-D atmospheric chemical transport model (GEOS-Chem). This algorithm was used in combination with the MODIS dense dark vegetation algorithm to retrieve 1 km HAOT over North China Plain from March to September of 2008. The values of the retrieved HAOT values are mostly between 0.7–3, with a correlation coefficient of 0.82 with the Aerosol Robotic NETwork observations and a 19% mean relative difference. Retrieval uncertainties associated with the errors in haze detection, surface reflectance, and haze models were analyzed using ground measurements.

Index Terms—Aerosol model, GEOS-Chem, haze aerosol optical thickness (HAOT), Moderate Resolution Imaging Spectrometer (MODIS), surface reflectance.

I. INTRODUCTION

THE NORTH China Plain, covering an area of about 409,500 km², is the largest alluvial plain of China. This region includes a cluster of large cities including Beijing, Tianjin, and Tangshan, and is one of the most densely populated areas in the world. The rapid economic growth and associated increase in fossil fuel consumption have caused a steady increase in particle concentrations, resulting in more frequent hazy days. Heavy haze has a large impact on the climate change [1] and environment. Haze also reduces the atmospheric visibility, resulting in traffic accidents and flight delays. The brownish haze consists of a mixture of anthropogenic sulfate, nitrate, organics, black carbon and fly ash particles, and natural aerosols such as sea salt and mineral dust [2]. In addition, fine particles have been linked to various adverse health outcomes such as childhood asthma, chronic obstructive pulmonary disease (COPD), bronchitis [3] and premature death [4].

The chemical and physical characteristics of haze in East Asia are commonly measured using ground measurements of particle concentrations and speciation, collocated with meteorological parameters [5], [6]. Ground-based lidars have been used to study the vertical structure of the haze [7]. However, point measurements lack the spatial coverage that is necessary to describe the spatial variability of regional haze. Given its broad coverage, satellite remote sensing can help to characterize haze’s spatial variability. With two sensors in orbit, and a swath width of over 2000 km providing nearly daily global coverage, MODIS is a candidate. For example, Lee et al. [8] used data from NASA’s MODIS sensors to study two haze events in Korea. Although satellite-measured AOT represents column averaged properties, they determined that high values of AOT corresponded to high values of PM₁₀ concentrations at the surface. Numerous other studies have successfully used the MODIS aerosol product to study particle concentration at the surface [9].

The MODIS operational “dark-target” aerosol retrieval algorithm (the dense dark vegetation (DDV) algorithm) is designed to infer clear-sky aerosol properties over land surfaces that have low values of surface reflectance in parts of the visible (VIS) and short-wave infrared (SWIR) spectrum. This algorithm removes the surface impact assuming a relationship of surface reflectance between the 2.1 μm band and the VIS bands (i.e., the “VISvs2.1” ratios). The VISvs2.1 surface reflectance relationship is parameterized as a function of both NDVI and scattering angle [10]. Since the impact of aerosol in the SWIR band is negligible, the surface reflectance in this band can be easily estimated. Then, the AOT could be derived by searching
the precomputed lookup tables correspond to different aerosol models [10]–[12].

However, there are cases where NASA-DDV algorithm cannot be applied, including conditions in which the 2.1 μm-band reflectance is so large (> 0.25) that it violates the assumption of “dark.” This may happen because the surface is bright, but also might happen when there is a heavy loading of large-particle dust particles [13], [14]. Since dust is often a component of haze in the region, the NASA-DDV algorithm is not very useful. Moreover, the thick aerosol layer over a pixel can completely obscure the surface features, causing the “VISvs2.1” surface reflectance relationship used in the DDV algorithm to be inapplicable [14]–[16]. Another difficulty is that aerosol size distribution and chemical composition during a haze event are often different from less polluted days [17], [18], and the default aerosol models included in the DDV algorithm may not be suitable. In recent years, atmospheric chemistry models have been shown to be able to improve satellite’s ability to estimate ground level particle concentrations [19]. A few studies have demonstrated that the global 3-D tropospheric chemistry and transport model data can significantly improve the MODIS’s capability of AOT retrieval [14], [20].

In this analysis, we present the development and validation of an AOT retrieval method for heavy haze events. Section II provides the description of the algorithm, which includes the identification of the haze, treatment of the surface reflectance, and the use of the haze aerosol model. Section III gives two examples of the retrieved haze AOT (HAOT) distribution in North China Plain in the spring and summer of 2008, the validation of this algorithm by using ground-based observations in Beijing, and the comparison with the MODIS DDV and Deep Blue product. Section IV analyzes the retrieving errors resulted from pixels identification, surface reflectivity, and aerosol model assumptions. Section V provides the conclusion.

II. DATA AND METHOD

Kaufman et al. [10]–[12] introduced the strategy for retrieving aerosol over land from MODIS. The top of the atmosphere reflectance (TOA) $\rho_{\text{TOA}}$ at a particular wavelength can be approximated by

$$\rho_{\text{TOA}}(\mu_s, \mu_v, \phi) = \rho_0(\mu_s, \mu_v, \phi) + \frac{T(\mu_s)T(\mu_v)\rho_s(\mu_s, \mu_v, \phi)}{1 - \rho_s(\mu_s, \mu_v, \phi)S} \quad (1)$$

where $\rho_0$ is the atmosphere path reflectance, $T$ is the transmission function describing the atmospheric effect on upward and downward reflectance, $S$ is the “atmosphere backscattering ratio,” and $\rho_s$ is the angular “surface reflectance.” These parameters ($\rho_0$, $T$, and $S$) are functions of solar zenith angle, satellite zenith angle, and solar/satellite relative azimuth angles ($\mu_s$, $\mu_v$, $\phi$). Except for the surface reflectance, each term on the right-hand side of (1) is a function of the aerosol type and AOT. The goal of our HAOT retrieval is to make the most appropriate assumptions about the surface reflectance and the aerosol model.

A. Surface Reflectance

The spatial and temporal features of the optical properties of land surface and aerosols are significantly different. Land surface is highly variable in space and changes little over a short period, whereas atmospheric aerosols can change rapidly over time but vary spatially on a larger scale of a few kilometers to tens of kilometers [21]. A haze event in North China Plain typically lasts less than one week. It usually occurs on a sunny day and forms as the air pollution worsens, followed by rapid visibility deterioration [22]. During this period, if there is no rain or snow, we can assume the surface reflectance in VIS wavelengths varies very slightly [23]. Moreover, since the surface contribution becomes less important due to high aerosol loading, we can also assume that the retrieval can tolerate slight surface reflectance variation during the period of a few days. Therefore, it is reasonable to use the surface conditions in the nearest low AOT days to represent surface conditions in the haze days. Based on these assumptions, the adjacent MODIS surface reflectance product reported in MOD09 was used for HAOT retrieval. High-level MODIS land products are generated if there are enough clear-sky observations available for a period. To minimize angular effects due to the non-Lambertian characteristic of the surface, we only selected pixels with lower view angle (< 30° [24]). The surface reflectance in pixels with larger view angle is derived from the MODIS bidirectional reflectance distribution function (BRDF) product (MOD43). The MOD43 product provides a set of coefficients that can be used for predicting reflectance at any given solar-viewing geometry. The surface bidirectional reflectance $R$ is described as follows:

$$R(\mu_s, \mu_v, \phi) = f_{\text{iso}} + f_{\text{geo}}K_{\text{geo}}(\mu_s, \mu_v, \phi) + f_{\text{vol}}K_{\text{vol}}(\mu_s, \mu_v, \phi) \quad (2)$$

where $K_{\text{vol}}$ and $K_{\text{geo}}$ are volume and geometric scattering kernels. A suitable expression for $K_{\text{vol}}$ was derived by Roujean et al. [25], while a suitable expression for $K_{\text{geo}}$ is the LiSparse non-reciprocal kernel [26], and they both are functions of solar zenith angle, satellite zenith angle, and solar/satellite relative azimuth angles ($\mu_s$, $\mu_v$, $\phi$). $f_{\text{iso}}$, $f_{\text{geo}}$, and $f_{\text{vol}}$ are three parameters and closely related to the biomass such as leaf area index, Lambertian reflectance, sunlit crown reflectance, and viewing and solar angles. The MOD09 and MOD43 products are generated using 8 days and 16 days of atmospherically corrected MODIS data on low-AOT days, respectively. However, if there are not enough cloud-free observations (e.g., multiday haze or cloudy events) to generate high quality products, we use the contemporaneous period of previous years. Based on these considerations, we created a surface reflectance database using 2006 ~ 2008 MODIS surface products.

Surface reflectance is wavelength dependent, with the values in the MODIS blue band for vegetated surfaces lower than other VIS wavelength. Some studies showed that there is a weaker surface BRDF effect over vegetated areas for blue wavelength [27], [28]. Here, we also use the blue wavelength surface reflectance for HAOT retrieval. Unlike the MODIS “Deep Blue” algorithm which is designed only for bright surfaces [24], [27], we mainly focus on high AOT events. The error associated to changing surface condition will be discussed in later sections.
B. Aerosol Model

Over the North China Plain, haze is mainly composed of fine particles of anthropogenic sources often occurring during summer monsoons and dust particles brought by spring dust storms [22], [29]. Hygroscopic particle growth can also alter aerosol optical properties quickly [30]. The DDV approach designates the aerosol models according to the AEROENT global classification. Despite the Aerosol Robotic NETwork (AERONET) has been grown rapidly over 100 sites worldwide, no observations were available in most regions over East China. Therefore, it is important to design an appropriate haze aerosol model for HAOT retrieval.

The haze aerosol model in our study are generated from a vector Second Simulation of a Satellite Signal in the Solar Spectrum (6S) radiative transfer code [31], which allows customized aerosol model with user-defined different particulate components. The vector 6S code also accounts for polarization to avoid substantial retrieval errors in blue wavelength [32]. Although the aerosol model can be estimated by ground observations [33], monitoring networks are sparse in China. Instead, we use the GEOS-Chem model to generate the haze aerosol model. The GEOS-Chem model (v8.3.2) can estimate sulfate, nitrate, ammonium, dust, carbon, and sea-salt aerosol mixing ratios (ppbv) at 3-h temporal resolution, 2° latitude × 2.5° longitude horizontal resolutions, and 37 vertical layers. Here, we use (3)–(6) to classify the different simulations into the dust-like, water-soluble, soot, and sea-salt components

\[
\text{Dust-like} = [DST_1] + [DST_2] + [DST_3] \tag{3}
\]
\[
\text{Water-Soluble} = f_{SO_4^2-}(\text{RH})[SO_4^2-] + f_{NH_4^+}(\text{RH})[NH_4^+] \tag{4}
\]
\[
+ f_{NO_3^-}(\text{RH})[NO_3^-] + [OCPI] \tag{5}
\]
\[
\text{Soot} = [BCPO] + [BCPI] \tag{6}
\]
\[
\text{Oceanic} = f_{SALA}(\text{RH})[SALA] \tag{7}
\]

where the \([DST_1] \) to \([DST_3] \) are dust particles with effective radii ranging from 0.7 μm to 2.4 μm; the \([SO_4^2-] \) (sulfate), \([NO_3^-] \) (nitrate) and \([NH_4^+] \) (ammonium) are the main components of water-soluble aerosols. \([OCPI], [BCPO], \) and \([BCPI] \) are hydrophilic organic carbon aerosol, hydrophobic, and hydrophobic black carbon aerosol, respectively. \([SALA] \) is the accumulation mode sea salt aerosol. 3-D relative humidity (RH) fields are directly obtained from the GEOS-Chem simulations. The aerosol size growth \(f_\varepsilon(\text{RH}) \) for the specie (x) is based on the equation of droplet growth factor described in Tang et al. [34] and the particle hygroscopicity study in North China Plain [30]. Tracer mixing ratios in each layer are integrated to the column aerosol information using the layer height. Application of the GEOS-Chem simulations in the North China Plain, and the validation of our aerosol model with ground-based observations will be discussed the following sections.

C. Haze Detection

A haze event is defined by World Meteorological Organization (2005) [35], as having 1) less than 10 km daily average visibility, excluding any other special events leading to low visibility, and 2) less than 80% daily RH. The main challenge of haze detection is to distinguish haze from bright targets such as non-vegetated surface, fog, low cloud, and thin cirrus. In the MODIS DDV algorithm, the non-cloud 500 m × 500 m pixels are further checked for their brightness, and 50% among the brightest pixels at 0.66 μm in each 10 km × 10 km scene are discarded. However, note that some of these bright pixels may be the haze pixels we would like to retrieve.

As a proof-of-concept analysis, we selected an example period from March 1 to September 30, 2008 to demonstrate our technique of haze identification. During this period, there are 129 record-days available in the AERONET Level 2 data set of Beijing and Xianghe stations. According to the local meteorological data in Beijing International Airport and Beijing Atmosphere Super Site (39.9° N, 116.1° E), there are 62 out of the 129 days when visibility was below 10 km and RH below than 80%, roughly corresponding to AERONET/AOT greater than 0.7. We randomly selected six (10%) haze events to analyze the TOA reflectance, brightness temperature in different MODIS wavelengths, and their combinations. The choice of MODIS bands is based on the spectral characterizers of haze, cloud, and regular aerosol. According to the analysis of these haze cases and literature on cloud detection [36]–[39], we established group thresholds to maximize reliable haze detection (Table I).

We used the near-infrared channels (e.g., \(R_{2.1} \)), the low-level water vapor strong absorption bands (e.g., \(R_{0.936} \)), and ratios of reflectance (e.g., \(R_{0.87}/R_{0.66}, R_{0.936}/R_{0.87} \)) to distinguish the haze from underlying land surfaces in each 1 km × 1 km box. Because haze is closer to the ground than clouds, the reflectance in VIS channels (e.g., \(R_{0.47}, R_{0.66} \)) for haze are usually lower

<table>
<thead>
<tr>
<th>Table I</th>
<th>MODIS USED BANDS AND THRESHOLDS FOR HAZE DETECTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>R and (2BT ) of MODIS bands used</td>
<td>Spectral range</td>
</tr>
<tr>
<td>R(1)</td>
<td>0.62–0.67μm</td>
</tr>
<tr>
<td>R(2)</td>
<td>0.84–0.87μm</td>
</tr>
<tr>
<td>R(3)</td>
<td>0.459–0.479μm</td>
</tr>
<tr>
<td>R(7)</td>
<td>2.105–2.135μm</td>
</tr>
<tr>
<td>R(18)</td>
<td>0.931–0.941μm</td>
</tr>
<tr>
<td>BT(20)</td>
<td>3.660–3.840μm</td>
</tr>
<tr>
<td>BT(22)</td>
<td>3.929–3.989μm</td>
</tr>
<tr>
<td>BT(26)</td>
<td>1.360–1.390μm</td>
</tr>
<tr>
<td>BT(31)</td>
<td>10.78–11.28μm</td>
</tr>
<tr>
<td>BT(35)</td>
<td>13.785–14.085μm</td>
</tr>
<tr>
<td>R(2)^2/R(1)</td>
<td>~</td>
</tr>
<tr>
<td>R(18)/R(2)</td>
<td>~</td>
</tr>
<tr>
<td>BT(20)^2-BT(22)</td>
<td>~</td>
</tr>
<tr>
<td>BT(22)-BT(31)</td>
<td>~</td>
</tr>
</tbody>
</table>

1(R(N)) is the TOA reflectance of MODIS band N; \(2BT \) is the brightness temperature calculated from Planck equation. \(^{37} \) is the ratio and difference of two band, respectively. \(^{37} \) is the ratio and difference of two band, respectively. \(^{37} \) is the ratio and difference of two band, respectively.
than those for low thick clouds, while the brightness temperatures for haze are higher than cirrus in infrared (e.g., $BT_{11}$, $BT_{13.9}$) and mid-infrared (e.g., $BT_{3.7}$) channels. In Table I, the haze distribution is only generated when the dependence of thresholds all matched. The errors related to using these thresholds to identify haze distribution will be analyzed in the following sections.

D. Diagram of the HAOT Retrieval

Fig. 1 illustrates the main steps of AOT retrieval algorithm on haze days. This algorithm is running on a pixel-by-pixel basis. The relevant Level 1B data include calibrated spectral reflectance and the associated geolocation information. The TOA reflectance were corrected for water vapor and ozone absorption followed MODIS DDV approach [10] by using the NCEP data, and organized into nominal 1 km × 1 km pixels.

1) The first step in our HAOT retrieval is to detect cloud, haze, and dark pixels. The cloud mask is generated from the MODIS cloud product (MOD35) and the spatial variability of the 0.47 μm and 1.38 μm channel reflectance [10]. The haze detection algorithm is described in Section II-C. To minimize the uncertainty of surface reflectance, only the pixels with the reflectance lower than 0.15 in 2.1 μm channel are masked as dark targets [33]. Cloud pixels are discarded, dark target pixels are processed using the operational MODIS DDV algorithm, haze pixels are retrieved using our HAOT algorithm. If haze happens on dark vegetated areas, we process it as haze pixels instead of using the DDV “VISvs2.1” surface reflectance relationship.

2) The second step is to generate atmospheric parameters including $\rho_0$ (path reflectance), $S$ (backscattering ratio), and $T$ (upward total transmission). Unlike the traditional LUT approach [10], we run the 6S radiative transfer code for each pixel. The input to 6S code includes the initial AOTs ($\tau_{0.55} = 0.01, 0.25, 0.5, 1, 1.5, 2, 2.5, \text{ and } 3$), user-defined aerosol model from GEOS-Chem mixing ratios, geometric conditions (month, days, solar, satellite zenith angle, and relative azimuth angles), target height and sensor altitude (satellite level), and spectral conditions of MODIS et al.

3) The third step is to compute modeled TOA reflectance using (1). The min value of $y$ from the cost function ($y = |\rho_{\text{TOA}} - \rho_{\text{TOA}}|$) is selected, then the corresponded initial AOTs are linearly interpolated to repeat Steps 1) and 2). The goal of a successful HAOT retrieval is to find the modeled TOA reflectance that best matches the MODIS TOA reflectance. In addition to the atmosphere parameters from step 2), the HAOT and DDV algorithms also differ in the treatment of surface reflectance. The surface reflectance in HAOT algorithm is calculated from the most adjacent clear-days MODIS surface product as described in Section II-A, while the DDV algorithm eliminates the surface impact based on the assumption of a relationship between 2.1 μm SWIR band and VIS channels.
III. RESULTS AND VALIDATION

A. Results

To illustrate the results of our HAOT retrieval algorithm, two haze episodes over North China Plain are used as examples. The first haze episode occurred between March 9 and 13, 2008. According to ground-based observation and local meteorological records in Beijing, this episode was caused by dust transported to the North China Plain from the Mongolian Plateau. In Fig. 2(a), the true-color satellite images clearly show the different colors between haze, cloud, and the surface. Normally, clouds are white, vegetated surfaces are dark, and haze appears brown (inside the red line) to our eyes. The haze distribution [Fig. 2(b)] shows that the haze layer covers a large area over the densely populated Hebei and Shandong provinces as well as Beijing and Tianjin metropolitan areas, where operational Terra MODIS AOT retrieval was not attempted [Fig. 2(c)]. The retrieved HAOT values range from 0.7 to 3 [Fig. 2(d)]. Over land, the blank areas without HAOT retrieval are due to cloud cover [e.g., left lower corner in Fig. 2(d)], or bright surface where neither the DDV algorithm nor our HAOT algorithm were applied.

The second haze episode shown here occurred on July 24, 2008. The southerly wind brings plenty of polluted fine particles to North China plain from highly industrialized coastal cities, and the air mass over land is blocked by Yanshan and Taihang mountains. The stable atmospheric structure often causes severe haze events with reduced visibility. These episodes can last several days until large-scale aerosol scavenging mechanisms such as precipitation occurs [22], [30]. As
shown in Fig. 3(a) and (b), the haze layer covers a large area including parts of Henan, Hebei and Liaoning provinces as well as Beijing and Tianjin metropolitan areas. The standard Terra MODIS product missed a large portion in the center of the haze layer [Fig. 3(c)]. Fig. 3(d) depicts the largest HAOI close to 3 in Beijing regions.

B. Validation

The MODIS standard AOT products have been validated against data from AERONET around the world and in China [15], and the estimated error is $\Delta \tau = 0.05 \pm 0.15 \tau$ [12]. There are two AERONET stations (i.e., Beijing and Xianghe) in North China Plain. As described Section II-C, we use the AERONET Level 2 data (accessed at http://aeronet.gsfc.nasa.gov) of the 62 recorded haze cases to validate our 1-km HAOI retrievals from Terra-MODIS. The ground observations within 1 h of the Terra satellite overpass were averaged in a 20 km $\times$ 20 km box (to avoid the mountain area where haze not frequently occurs) centered around each AERONET site. Fig. 4(a) compares our retrieved HAOI with AERONET observations.

Linear regression of our retrieved MODIS HAOI against the AERONET observations yields an $R^2$ of 0.82, a mean relative difference ($|\tau_{\text{OurWork}} - \tau_{\text{AERONET}}|/\tau_{\text{AERONET}}$) of 19%. We obtained the haze detection thresholds from 6 (10% of 62) haze cases in Beijing and used the remaining 90% of the data to test the algorithm. The matched number ($n = 49$) corresponding to the total 62 haze cases means 79% haze days are detected by our approach and 61% of data points are within the error range of $\Delta \tau = 0.05 \pm 0.15 \tau$. The correlation coefficient is higher at...
greater AOT levels (> 1.5) (No. obs = 20, and 85% data points are within the two dashed lines). On the contrary, the relative error is larger when the AOTs ($\tau$) < 1, which may be mainly due to uncertainties in estimated surface reflectance for thin haze. In comparison, the $R^2$ and relative differences between AERONET and MODIS DDV product are 0.65 and 27%, respectively. Moreover, the DDV algorithm detects substantially less haze cases (29), and there is no retrieval in Deep Blue data set (Collection 5.1) over North China Plain during this period.

IV. UNCERTAINTY ANALYSIS AND DISCUSSION

The uncertainties in our HAOT algorithm may be attributed to haze detection, surface reflectance estimation, and the construction of haze aerosol model. These three factors are discussed in the following sections.

A. Impact of Haze Detection

Since haze is similar to bright targets in reflectance and brightness temperature in both the VIS and infrared channels, some bright targets such as non-vegetated surfaces could be misclassified as haze pixels. To minimize the error in haze detection, we removed pixels with lower AOT value (< 0.7) from haze distribution after the retrievals, because 1) HAOTs are usually larger than 0.7 according to Beijing’s ground-based observations, 2) mixing height is usually around 1 km in North China Plain in late morning, indicating there are few cases that the aerosol is all in a very thin layer near the surface, 3) the lower AOTs will lead more uncertainties if using adjacent surface reflectance for retrieval. Another difficulty is to separate accurately haze from the thin/low clouds. The identification of haze refers to the literatures on cloud detection, while in MODIS Cloud Mask products (MOD35), there are four confidence levels [37]. Our analysis shows that haze is usually misidentified under probably clear and uncertain cloudy conditions (0.66 < confidence < 0.95). We also removed the larger cloud optical thickness (OT > 3) from the haze distribution. Because haze detection thresholds are set according to the special cases in Beijing, it is likely to cause errors in haze detection over other areas. Further improvements to large-scale haze detection are the focus of our future research.

B. Impact of Surface Reflectance on HAOT Retrieval

Some studies show errors of 0.01 in assumed surface reflectance lead to errors on the order of 0.1 in AOT retrieval [11]. Using the nearest sunny-days reflectance or historical data to replace the haze-day value, the variation of surface condition and observation geometry will affect the final HAOT results. To examine the impact of surface reflectance, we selected three 50 km × 50 km boxes in the Beijing-Tianjin-Tangshan region over North China Plain, which represent three main surface
Fig. 6. Variation of surface reflectance in blue band over north China plain in the year of (a) 2006, (b) 2007, and (c) 2008; the difference of surface reflectance in adjacent 8 days in (d) 2006, (e) 2007, and (f) 2008; and the variation of surface reflectance in different years of (g) 2006–2007, (h) 2007–2008.

As shown in Fig. 6(a)–(c), the blue band (0.47 μm) surface reflectance from 2006 to 2008 in this region shows significant seasonal variation, with highest values in winter due to lack of vegetation. As expected from the vegetation cover, urban areas have the highest surface reflectance (the mean value in 3 years is \( \sim 0.058 \)), followed by rural (\( \sim 0.052 \)) and mountain areas (\( \sim 0.032 \)).

To check the surface variation in a haze event, we calculate the reflectance difference using the adjacent 8 days MODIS data. Approximately 75% of the reflectance differences are less than 0.01, and only 4% is greater than 0.02 [Fig. 6(d)–(f)]. The difference is mostly caused by the weather such as snow or rain.

To check the surface variation on the same day from different years, we calculate the reflectance difference using the adjacent 2 years MODIS product. As expected, the interannual variation is more pronounced than that calculated using adjacent 8 days from the same year, about 29% is greater than 0.01, and 6% is greater than 0.02 [Fig. 6(g) and (h)]. In addition to weather, other factors such as land cover change and vegetation growth change also contribute to the differences.

To check the surface variation with different view angles, the MCD43 BRDF parameters products from 2006 to 2008 were processed using (2). Fig. 7 is the maximum difference of surface reflectance when satellite zenith angle changes from 0° to 60°. Approximately 70% of the reflectance differences are less than 0.02, and only 12% is greater than 0.03. As shown in Fig. 7, urban and mountain areas give greater non-Lambertian behavior than rural areas, particularly in winter with sparse vegetation cover, which means the land cover and terrain have a large impact on the BRDF effect [40]. Most of North China...
Fig. 7. Maximum difference of surface reflectance (blue band) with view angular variation (0°–60°) over (A) urban, (B) rural, and (C) mountain distinct of Beijing in the year of (a) 2006, (b) 2007, and (c) 2008.

TABLE II

<table>
<thead>
<tr>
<th>Variation of Surface Reflectance</th>
<th>Variation of HAOT</th>
<th>1&lt;HAOT ≤1.5</th>
<th>1.5&lt;HAOT ≤2</th>
<th>2&lt;HAOT ≤2.5</th>
<th>HAOT&gt;2.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.001</td>
<td>-0.001</td>
<td>-0.004</td>
<td>-0.009</td>
<td>-0.008</td>
<td>-0.003</td>
</tr>
<tr>
<td>0.005</td>
<td>-0.005</td>
<td>-0.025</td>
<td>-0.044</td>
<td>-0.035</td>
<td>-0.018</td>
</tr>
<tr>
<td>0.01</td>
<td>+0.01</td>
<td>-0.048</td>
<td>-0.092</td>
<td>-0.071</td>
<td>-0.037</td>
</tr>
<tr>
<td>0.02</td>
<td>+0.02</td>
<td>-0.11</td>
<td>-0.2</td>
<td>-0.15</td>
<td>-0.086</td>
</tr>
<tr>
<td>0.03</td>
<td>+0.03</td>
<td>-0.16</td>
<td>-0.31</td>
<td>-0.24</td>
<td>-0.15</td>
</tr>
<tr>
<td>0.05</td>
<td>-0.03</td>
<td>0.14</td>
<td>0.12</td>
<td>0.068</td>
<td>0.019</td>
</tr>
<tr>
<td>number of haze pixels</td>
<td>30,053</td>
<td>2,843</td>
<td>7,187</td>
<td>12,760</td>
<td>5,362</td>
</tr>
</tbody>
</table>

Plain is covered by yellow clay soil and crops including wheat, rice, corn, and cotton. Previous BRDF experiments in China [41] showed within 0.02 errors to most vegetation and soil types in blue band, and the observation geometry accounts for <40% absolute errors to trees [42]. Moreover, the majority of North China Plain has an elevation of less than 50 m above sea level, which has a weak surface BRDF effect compared to more complex terrains. In this analysis, because our haze cases all occurred from March to September, both mountain and urban areas show lower surface reflectance and smaller non-Lambertian behavior during this period. Therefore, the total errors of surface reflectance due to the impact of view angles are likely to be less than 0.03.

To test our hypothesis, we examined the two cases on March 11 and July 24, 2008 discussed in Section III-A, where there are more than 30,000 haze pixels. Here, we set the change of surface reflectance in 0.001, 0.005, 0.01, 0.02, 0.03, and 0.05 in the retrievals to estimate retrieval errors. The corresponding variations of HAOT are shown in Table II.

As expected, HAOT is overestimated if reflectance is underestimated, and vice versa. As HAOT increases from <1 to > 2.5, the HAOT retrieval error decrease, and the error is insignificant for thick haze with HAOT > 2. The contribution from the surface reflectance becomes less important for the heavier HAOT, and the retrieval can tolerate the surface reflectance variation with the HAOT increasing.

As shown in Table II, minor changes in surface reflectance (0.001 and 0.005) have almost no impact on HAOT retrieval; the error of ~0.01 in surface reflectance can lead to ~0.05 retrieval error. Given a reflectance change of 0.03 caused by different surface conditions and observation angles, HAOT retrieval errors are still within the range of Δτ = ±0.05 ± 0.15τ. Our analysis indicates that the impact of surface reflectance is significantly lower than that in less polluted conditions because of the high HAOT values. If the surface is affected by rain or snow in adjacent 8 days, land use change in different years, or large observation angle changes, the reflectance error will be larger than 0.05 introducing greater uncertainty in HAOT.
C. Impact of Aerosol Model on HAOT Retrieval

We calculated the volume percentage of four major aerosol components based on GEOS-Chem simulations and fed them to the 6S code. Unlike the traditional predefined look-up table approaches, the dynamic atmospheric chemistry and transport model data may better reflect the spatiotemporal variability of aerosols.

As shown in Fig. 8, haze is mainly composed of dust-like and water-soluble particles and shows strong spatial variability over the North China Plain. The aerosol model in the northwest is dominated by dust-like particles, particularly in some semi-arid regions (> 50%). The water soluble aerosol is controlled by the Asian monsoon and is high (> 60%) in the southeast regions. The percentage of soot and sea-salt aerosols are smaller (< 10%). However, one of the deficiencies of the GEOS-Chem model is the coarse horizontal resolution (2° latitude × 2.5° longitude). In this analysis, both the clean and hazy days’ aerosol model are simulated by the GEOS-Chem data, so there is no difference between haze and adjacent assumed “dark target” in one grid. In our future work, we will conduct GEOS-Chem nested runs (0.5° latitude × 0.667° longitude) to improve horizontal resolution.

In order to check the accuracy of GEOS-Chem simulated mixing ratios, the aerosol model are recalculated based on Li’s method as

\[
\left(\rho_{\text{TOA, Blue}} - \rho_{\text{TOA, Blue}}\right)^2 + \left(\rho_{\text{TOA, Red}} - \rho_{\text{TOA, Red}}\right)^2 < \varepsilon. 
\] (7)

This method computes the TOA reflectance at two VIS bands, with AERONET AOT observations and different aerosol components as the input to 6S radiative code. The goal of
successful aerosol model simulation is to find the two modeled TOA reflectance ($\rho^\text{TOA-Blue}_{\text{TOA-Red}}$, $\rho^\text{TOA-Red}_{\text{TOA-Red}}$) that both better matches the corresponding MODIS-observed TOA reflectance ($\rho^\text{TOA-Blue}_{\text{TOA-Red}}$, $\rho^\text{TOA-Red}_{\text{TOA-Red}}$).

From March to September, 2008, we collected AOT at Beijing and Xianghe AERONET sites (black dots in Fig. 8), and set 5% increments between different components to simulate the aerosol components. We found the haze aerosol model in the 62 cases is best characterized by using the volume fractions of $\sim35\%$ dust like, $\sim60\%$ water soluble, $\sim5\%$ soot, and $\sim0\%$ oceanic. Correspondingly, the GEOS-Chem’s aerosol volume percentage in Beijing region (black box in Fig. 8) during this period is 43.4% dust like, 52.7% water soluble, 3.8% soot, and 0.01% oceanic particles. Compared to the ground-based simulations, the fractions of dust-like and water-soluble particles in the haze model change less than 10%, and the soot and oceanic particles are almost the same. These small discrepancies will account for $<10\%$ absolute errors for the HAOT retrievals [43]. In addition, many studies [14], [19], [20] have shown the applicability of GEOS-Chem simulations, also indicating that the aerosol model used in our algorithm is acceptable.

V. CONCLUSION

We developed an algorithm to retrieve HAOT at 1 km spatial resolution using various MODIS data under heavy particle pollution conditions. This algorithm assumes that the change of surface reflectance is small in a few days before the haze event, and the surface reflectance from the most adjacent clear-days can be used to estimate surface contribution. The assumption of slow changes in land surface is similar to the MAIAC algorithm [23], which using the multi-angle ideas to retrieve AOT and surface reflectance simultaneously. However, our approach is easier to combine with the DDV algorithm. For most sunny conditions, we still use the MODIS DDV algorithm. In fact, our approach resembles the Deep Blue algorithm, but with the following improvements: 1) dynamic surface database, 2) expanded coverage to urban areas, and 3) the heavy haze conditions. This analysis attempts to make progress on the above three items and apply it in North China. Examination of the variation of the surface reflectance with time and the error in BRDF on the retrieval of HAOT indicates that using the nearest clear-days’ MODIS surface reflectance product, and even using that in the same period of the previous year to represent the reflectance under haze days is usually acceptable. Based on GEOS-Chem simulated aerosol mixing ratios, haze aerosol models corresponding to different particle compositions has been computed using 6S codes. The GEOS-Chem simulations indicate haze over North China Plain is mainly composed of coarse particles from natural dust and water-soluble fine particles. The validation using ground-based measurement also shows the haze aerosol model in our algorithm is acceptable.

Comparison with AERONET AOT measurements in Beijing from March to September, 2008 showed better agreement between our retrieved HAOT values and ground truth than operational MODIS AOT retrievals. In addition, our algorithm extends the spatial coverage of MODIS AOT into very high AOT values (0.7 $\sim$ 3.0). This to a large extent avoids the low sampling bias in high AOT regions, enhancing MODIS’s ability to monitor particle pollution in many large urban areas in developing countries with frequent severe air pollution episodes due to dust transport, fossil fuel combustion, and biomass burning.

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