Dust Aerosol Retrieval Over the Oceans With the MODIS/VIIRS Dark-Target Algorithm: 1. Dust Detection

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Abstract To prepare for implementation of a new aerosol retrieval specifically designed for dust aerosol over ocean in the operational Dark-Target (DT) algorithms for the Moderate-resolution Imaging Spectrometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) satellite sensors, we focus on the challenge of detecting dust. We first survey the literature on existing dust detection algorithms and then develop an innovative algorithm that combines near-UV (deep blue), visible, and thermal infrared (TIR) wavelength spectral tests. The new detection algorithm is applied to Terra and Aqua MODIS granules and compared with other dust detection possibilities from existing MODIS products. Quantitative evaluation of the new dust detection algorithm is conducted using both a collocated AERONET-MODIS data set and collocated Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO)-MODIS data set. From comparison with both AERONET and CALIOP measurements, we estimate the new dust detection algorithm detects about 30% of weakly dusty pixels and more than 80% of heavily dusty pixels, with false detections in the range of 1–2%. The very low false detection rate is particularly noteworthy in comparison with existing literature. Compared with the dust flag currently available as part of the MODIS cloud mask product (MOD35/MYD35), and dust classification based on commonly used thresholds with aerosol optical depth (AOD) and Angstrom exponent (AE), the new dust detection algorithm finds more dusty pixels and fewer false detections.

Plain Language Summary The Dark-Target (DT) aerosol retrieval is applied to measurements from the Moderate-resolution Imaging Spectrometer (MODIS) on the Terra and Aqua satellites to retrieve spectral aerosol optical depth (AOD) over land and ocean. The algorithm generally provides high-quality retrievals within specified error bars. However, the DT-Ocean algorithm tends to provide biased retrievals of AOD, Angstrom exponent (AE), and fine mode fraction (FMF) for scenes containing dust aerosol of African or Asian origin. These biases are scattering angle dependent, which suggests errors in the assumed optical properties and phase function from the spherical dust models used. Therefore, we aim to improve the DT retrieval of dust over ocean with a two-step strategy. Here in Part 1, we describe Step 1 in which we develop an innovative dust detection algorithm that combines deep-blue, visible, shortwave infrared, and thermal infrared wavelength spectral tests that are based on a survey of existing dust detection algorithms. Step 2 is described in Part 2, where we develop new nonspherical dust models and apply it to identify heavy dust pixels. Combining dust detection and nonspherical dust model has led to significant improvements in retrieved AOD, AE, and FMF in dust regions.

1. Introduction

Mineral dust aerosols arise from windblown soils and have a multitude of impacts on weather and climate, air quality, public health, and ecosystems. Dust aerosol affects global and regional climate through direct radiative forcing and indirect interaction with cloud and precipitation processes (Miller and Tegen, 1998; Harrison et al., 2001; Kaufman et al., 2002; Kok et al., 2018; Rosenfeld et al., 2011; Shell and Somerville, 2007; Yu et al., 2006; Zhao et al., 2011). Dust aerosols can significantly impact air quality and the human respiratory system (Griffin, 2007; Goudie, 2014). Heavy dust storms can impair local transportation and cause damage to infrastructure and crops (Goudie & Middleton, 2006; Prospero & Lamb, 2003; Weinzzierl et al., 2012). Mineral dust originating from one region can be transported thousands of kilometers downwind, impacting air quality and ecosystems far beyond its source region (Gaiero et al., 2013;
Gassó et al., 2010; Hsu et al., 2006; Kaufman et al., 2005; Kim et al., 2014; Prospero et al., 2014; Yu et al., 2013; 2015). Characterizing global dust distribution is thus very important for climate studies as well as air quality monitoring. Dust aerosol is particularly complex as these particles have a wide range of sizes, shapes, and mineralogical compositions, depending on the source region and meteorological conditions. Dust entrained into the atmosphere from a source region is subject to many changes during its thousands of kilometers transit as mixing, humidification, and deposition of large particles take place.

As dust is so complex, satellite remote sensing provides the global observations for characterizing global dust distribution. Remote sensing of dust or other aerosol particles is commonly performed by using the spectral signatures in observed radiances that arise from the interactions between the light and the atmospheric particulates. The size, shape, and chemical compositions of particles determine their absorption and scattering properties and consequently the radiances received by a remote sensing instrument. These measurements, when converted into either reflectance in the ultraviolet (UV), visible, or near-infrared (NIR) channels or brightness temperature in the infrared (IR), are used to infer the columnar integrated mass and optical properties of the particles. However, in addition to the dust we are trying to observe, factors such as surface reflectivity, clouds, and other types of aerosols and molecular scattering contribute to the spectral signatures received by the sensors. Thus, identifying dust and retrieving its optical properties is a great challenge.

The Moderate-resolution Imaging Spectrometer (MODIS) instruments on board the Terra and Aqua satellites have been observing the Earth’s cloud, aerosol, and surface since their launches in 2000 and 2002, respectively. MODIS comprises 36 spectral channels from 0.41 to 15 μm with a nominal (nadir) resolution of 250, 500, or 1,000 m at nadir depending on band and has a swath width of approximately 2,300 km. For aerosol retrievals, currently there are three operational retrieval algorithms, namely, Dark-Target (DT; Levy et al., 2013), Deep Blue (DB; Hsu et al., 2019), and Multiangle Implementation of Atmospheric Correction (MAIAC; Lyapustin et al., 2018), all developed at NASA’s Goddard Space Flight Center.

The DT aerosol retrieval algorithm consists of two independent components, one for ocean (DT-O; Levy et al., 2013; Remer et al., 2005; Tanré et al., 1997) and one for the dark land surfaces such as vegetation (DT-L; Levy et al., 2007; Levy et al., 2010, 2013). The DT algorithm relies on observing the contrast (and spectral dependence) of aerosol reflectance over dark surfaces and oceans. The algorithm (both land and ocean) follows a lookup table (LUT) approach; that is, the top-of-atmosphere (TOA) spectral reflectance is precalculated using scattering and radiative transfer (RT) codes (Ahmad and Fraser, 1982; Dubovik et al., 2002; Evans and Stephens, 1991; Wiscombe, 1980) for predefined aerosol, surface, and atmospheric properties. The ocean LUTs contain four fine aerosol models and five coarse models, in an effort to represent all aerosol types. The DT-O retrieval algorithm selects one fine mode and one coarse mode aerosol with an adjustable fraction that minimizes the difference between the LUT reflectance and observed TOA reflectance in six wavelengths (0.55, 0.65, 0.86, 1.2, 1.6, and 2.13 μm). The retrieved quantities include total aerosol optical depth (AOD at 0.55 μm), Angstrom exponent (AE) derived from the AOD at 0.55 and 0.86 μm, and a fine mode fraction (FMF) that estimates the relative mixing between the fine mode and coarse mode aerosols.

Dust aerosols are predominantly nonspherical in shape (Chou et al., 2008). The DT-L has incorporated a nonspherical dust model (Levy, Remer & Dubovik, 2007). However, the current MODIS DT-O algorithm still does not have a nonspherical dust model, which creates bias in the retrieved AOD, FMF, and AE (shown in Part 2, Zhou et al., 2020). While it may be tempting to simply add to the DT-O algorithm’s current spherical coarse models with new models corresponding to nonspherical particles (without changing the rest of the algorithm), it does not work. Choosing the right dust model is not trivial as dust particles can take on different sizes, shapes, and chemical compositions and an ill-represented dust model may make the retrieval worse. Additionally, there is no guarantee that the algorithm would reliably choose nonspherical models for dust and spherical models for nondust aerosol, possibly further degrading the results of the retrieval.

Therefore, our strategy is to use two steps, that is, first identify likely dust pixels, and then retrieve the AOD, AE, and FMF using an appropriate dust model. In this Part 1 paper, we focus on dust detection and organize as follows. Section 2 describes the data used in this work. Section 3 reviews dust detection in the current literature and summarizes our new dust identification algorithm. Section 4 evaluates the new dust detection algorithm with sample granules, and by collocating and comparing to ground-based Sun photometer and satellite-based lidar data. Section 5 shows the global dust distribution in two dust heavy months. A brief summary and discussion is provided in section 6.
2. Data

The primary data used in the study are MODIS Level 1B calibrated TOA reflectance products (MxD02) (http://mcst.gsfc.nasa.gov/content/11b-documents) and Collection C6 Level 2 aerosol products MxD04 (Levy et al., 2013) (where x is substituted by O for Terra and Y for Aqua). The MxD02 contains reflectance and radiance data at three native resolutions (i.e., 0.25, 0.5, or 1.0 km at nadir, depending on band), whereas the DT algorithm aggregates these observations into 3 x 3 or 10 x 10 boxes as retrieval units. The MxD04_L2 products used here include AOD, AE, and FMF reported at 10 x 10 km (nadir) resolution. In addition to the retrieved aerosol properties, a MxD04 data point contains the clear-sky reflectance values used in the retrieval, quality assurance (confidence) estimates, as well as other ancillary information such as 2-m surface wind speed from National Centers for Environmental Prediction (NCEP) reanalysis. We also use many of the individual cloud tests and especially the dust flag from the standard MODIS cloud mask product MxD35 (reported at 1 km resolution).

Aerosol measurements from the ground-based Aerosol Robotic Network (AERONET) Sun photometers are commonly used for validating satellite aerosol retrievals. AERONET is a global network of Cimel Electronique CE-318 Sun-sky radiometers with between four and nine spectral channels. AOD is obtained from direct Sun measurements most often at 0.34, 0.38, 0.44, 0.50, 0.67, 0.87, and 1.02 μm with frequency of every 15 min; The high accuracy of AERONET AOD (estimated errors of ~0.01–0.02) makes it widely popular (Eck et al., 1999; Holben, 1998). In addition to direct Sun measurements, the instruments measure the sky radiance in four spectral bands (0.44, 0.67, 0.87, and 1.02 μm) along the solar principal plane up to nine times a day and along the solar almucantar up to eight times a day. Measurements from almucantar scans are used to retrieve aerosol particle size distribution, spectral complex refractive index, and single scattering albedo (SSA) (Dubovik & King, 2000; Dubovik et al., 2006). The majority of traditional AERONET stations are situated inland, with some located near the coast, and a few at small islands in the middle of the ocean. In this work, we use the latest Version 3 products, which provides improved cloud screening and better identification of heavy aerosol events (Giles et al., 2019).

To match the MODIS retrievals with the AERONET measurements, AERONET measurements within ±30 min of the MODIS overpass time are averaged and compared against the values for all the MODIS retrieved pixels located within 0.3° radius of AERONET stations (Shi et al., 2019). In this way there are many collocations reported at each AERONET location at every overpass opportunity, since the AERONET observations are averaged to a single value but the many MODIS retrieved pixels within the matchup circle are not. The MODIS (both Aqua and Terra)-AERONET collocation data from 2011 will be used for evaluation of the new dust detection algorithm. AERONET AOD at 0.55 μm is lineally interpolated in log-log space from measurements at 0.44 and 0.67 μm (i.e., fit by AE) to be compared with MODIS AOD at 0.55 μm. We use the AERONET AOD and AE measurements to identify likely dust situations and compare with the result of the new dust detection algorithm applied to MODIS pixels in near proximity to the AERONET station.

Aerosol measurements from space-borne active sensors such as the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) on board the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) (Winker et al., 2013) are frequently used to evaluate the performance of dust detection algorithm designed for passive sensors (Burton et al., 2013; Ciren & Kondragunta, 2014). CALIPSO was a key member of the Afternoon Constellation of satellites (A-Train) from 2006 to 2018, measuring backscattering profiles at a 30-m vertical and 333 m along-track resolution at wavelengths of 532 and 1,064 nm (Winker et al., 2013). CALIOP also measures the perpendicular and parallel signals at 532 nm, along with the depolarization ratio at 532 nm that is frequently used in aerosol/cloud phase discrimination algorithms because of its strong particle shape dependence. The CALIOP Version 4 Level 2 5-km Cloud/Aerosol Layer products not only provide discrimination between cloud and aerosol but also a qualitative assignment of aerosol type in each vertical layer, that is, “clean marine,” “dust,” “smoke,” “polluted dust,” “dusty marine,” “polluted continental/smoke,” “elevated smoke,” and “undetermined.” A MODIS-Aqua/CALIOP collocated data set is generated with a strict algorithm that fully considers the spatial differences between the two instruments and parallax effects, as described in Holz et al. (2008). We consider various numbers of CALIOP-identified pure dust aerosol layers in the vertical column to identify dusty pixels that should be detected by the new algorithm applied to MODIS measurements. Note that when we say that a pixel or a scene is “dusty,” we mean that it has been identified as likely containing dust aerosol somewhere within the horizontal or vertical domain.
3. Developing a Dust Detection Algorithm for MODIS

3.1. Current Dust Detection Techniques

Many dust detection algorithms have been developed utilizing specific optical properties of dust in the UV (Herman et al., 1997), visible (Jankowiak and Tanré, 1992; Kaufman et al., 1997; Martins et al., 2002; Miller, 2003), and IR (Cho et al., 2013; Evan et al., 2006; Zhao et al., 2010) spectral regions. The Absorption Aerosol Index (AAI) derived from Total Ozone Mapping Spectrometer (TOMS) and Ozone Monitoring Instruments (OMI) is a UV-based technique that utilizes the strong absorption of dust and smoke and low-surface reflectivity in UV spectral regions (Herman et al., 1997; Torres et al., 1998, 2007). The AAI relies on the relatively small spectral variations in two UV channels (0.354 and 0.388 μm) in the presence of absorbing aerosols as compared to rapid change of Rayleigh scattering in these channels. A dust aerosol index (DAI) computed from slightly longer wavelength in deep-blue and blue channels (0.412 and 0.490 μm) is employed by the DB aerosol retrieval algorithm for SeaWIFS and MODIS instruments to screen cloud scenes over bright surface (Hsu et al., 2004). Setting a higher threshold for DAI prevents misidentification of dust scenes and cloud. A recent U.S. National Oceanic and Atmospheric Administration (NOAA) dust detection algorithm utilizes DAI as a first step to separate absorbing aerosols (dust and smoke) from nonabsorbing aerosols (Ciren & Kondragunta, 2014). NOAA’s DAI is computed from two close channels in 0.412 and 0.440 μm to minimize reflectance changes in surface. Neither AAI or DAI can separate dust from other absorbing aerosols such as smoke. Hence, NOAA’s dust detection algorithm further uses a NonDust Absorbing Aerosol Index (NDAI), computed from the spectral ratio of 0.412 and 2.13 μm channels to separate dust from smoke. The NDAI capitalizes on the fact that dust particles have higher reflectivity in the 2.13 μm band than smoke particles as a result of their larger size. However, the differences in surface reflectance between the two wavelengths are not taken into consideration.

In the visible and NIR wavelengths, since dust is visually brighter than most dark surfaces, that is, ocean and vegetation, but darker than cloud and sometimes desert, reflectance in visible channels (0.47, 0.65, and 0.87 μm) make good first-order tests for dust scenes in locations where dust is expected (Jankowiak & Tanré, 1992; Kaufman et al., 2000; Miller, 2003; Tanré and Legrand, 1991). More sophisticated techniques use the different spectral variations of dust absorption and scattering in contrast to surface and cloud reflectance ratios between blue, red, and green channels (i.e., 0.47/0.65, 0.65/0.55, and 0.55/0.47 μm) or normalized reflectance difference such as the normalized difference vegetation index (NDVI) have been used for dust detection (Jankowiak & Tanré, 1992; Miller, 2003; Zhao et al., 2010). A step further in this application is combining a visible channel with a shortwave infrared (SWIR) channel (i.e., the NDAI from Ciren & Kondragunta, 2014, uses the ratio of 0.47 and 2.13 μm, and Qu et al., 2006, uses normalized spectral difference between 2.13 and 0.47 μm) to maximize the difference in spectral contrasts.

In the IR window region, the different refractive indices of dust in 11 and 12 μm are used as the basis for brightness temperature difference (BTD) test to distinguish dust from clouds (Bullard et al., 2001; Shenk & Curran, 1974; Sokolik, 2002; Wald et al., 1998). Both the real and imaginary refractive indices of dust are higher in 11 μm than in 12 μm, while it is the opposite for an ice cloud. Thus, the difference BTD 11–12 μm is expected to be negative for dust and positive for ice cloud. For the water-clouds, the differences in real and imaginary refractive indices are such that they cancel out, leaving BTD 11–12 μm close to 0. Some algorithms use 8.5 μm in addition to 11 and 12 μm (trispectral) differencing for dust detection (Ackerman, 1989, 1997; Ashpole and Washington, 2012; Hansell et al., 2007; Hu et al., 2008; Schepanski et al., 2007; Strabala et al., 1994). Since brightness temperature not only depends on the optical properties of aerosols but also on surface emissivity, vertical profiles of atmosphere, aerosol distribution, and water vapor, the IR technique is found to be highly dependent on regions (Hansell et al., 2007).

In addition to single pixel tests, spatial and temporal features of dust have also been used to separate dust from clouds and surface (Darmenov and Sokolik, 2009; Jankowiak & Tanré, 1992; Martins et al., 2002). For example, spatial variability (i.e., pixel-to-pixel) tests in 0.86 or 0.64 μm are often used to separate dust from clouds as dust appears more spatially homogenous than clouds. The Infrared Differential Dust Index (IDDI) uses temporal and spatial difference of IR temperature in dusty pixels and clear pixels (Legrand et al., 2001) to detect dust. A summary of dust detection algorithms is listed in Table 1. Not all of the tests are available for every instrument since each instrument has a limited number of spectral channels.
### Table 1

**Review of Plausible Dust Optical Properties From Previous Works**

| Names                        | Tests                                                                 | References                                                                                       |
|------------------------------|-----------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|
| IR split window              | BTD 11–12 μm; BTD 8.7–11 μm                                           | Shenk and Curran (1974); Strabala et al. (1994); Ackerman (1989, 1997); Legrand et al. (1989, 2001); Wald et al. (1998); Legrand et al. (2001); Sokolik (2002); Darmenov and Sokolik (2005); Roskovensky and Liou (2005); Evan et al. (2006); Schepanski et al. (2007); Hao and Qu (2007); Hansell et al. (2007); Hu et al. (2008); Bullard et al. (2008); Ashpole and Washington (2012) |
| SWIR                         | 3.76 μm; 3.76–11 μm                                                   | Legrand et al. (2001); Qu et al. (2006); Ciren and Kondragunta (2014)                            |
| NIR                          | 1.64 and 2.13 μm                                                       | Tanrê and Legrand (1991); Kaufman et al. (2000); Miller (2003); Qu et al. (2006); Jankowiak and Tanrê (1992); Zhao et al. (2010) |
| Visible                      | ρ at 0.47, 0.55, 0.67, and 0.86 μm; 2-channel ratio: ρ1/ρ2; normalized difference ratio: (ρ1 − ρ2)/(ρ1 + ρ2) | Herman et al. (1997); Torres et al. (1998, 2007); Hsu et al. (2004); Ciren and Kondragunta (2014) |
| Deep blue, UV                | −10 * [Log (ρ0.41/ρ0.47) − log (ρ0.41/ρ0.47)]; −10 * [Log (ρ0.41/ρ0.44) − log(ρ0.41/ρ0.44)] | Tanrê and Legrand (1991); Jankowiak and Tanrê (1992); Martins et al. (2002); Darmenov and Sokolik (2009) |
| Spatial variability/Spatial/temporal contrast with clear sky | ρ at 0.87 and 0.64 μm                                                 |                                                                                                |

Since MODIS provides many spectral channels ranging from deep blue, visible to NIR and thermal infrared (TIR), there are numerous spectral choices for dust detection. Previous efforts in combining multiple visible and IR spectral tests have led to many multichannel dust detection algorithms (e.g., Cho et al., 2013; Evan et al., 2006; Hansell et al., 2007; Lee, 1989; Roskovensky & Liou, 2005; Zhao et al., 2010). Among these, Zhao et al. (2010) is implemented with the standard MODIS cloud mask (MOD35) to detect heavy dust that could potentially be identified as cloud, and a dust flag is reported along with other cloud mask tests. The algorithm combines multiple visible and IR channels and spatial variability in the reflectance at 0.86 μm to detect heavy dust. Initial evaluation of the algorithm shows that the algorithm succeeds in detecting heavy dust plumes near the source regions but misses thin dust far away from source regions (Cho et al., 2013; Zhao et al., 2010). In addition, the algorithm miss identifies many dusty pixels in high-latitude oceans.

Dust detection accuracy from major existing algorithms ranges from 60% to 84% depending on regions with false detection rate of about 20% when compared to dust detection from CALIPSO (Ciren & Kondragunta, 2014; Cho et al., 2013). These studies show that current dust detection algorithms could be good at detecting either thick dust, but when faced with thin dust, they allow a large number of false detections.

As an alternative method for MODIS, we might use retrieved parameters from the DT aerosol algorithm (AOD, AE, and FMF) to identify pixels that are likely “dusty.” In general, dust aerosols can be distinguished from background marine aerosol and other pollution and smoke aerosols by their large AOD, small AE, and small FMF due to the larger particle sizes, if the retrieval is done correctly. A simple evaluation of the approach is done by comparing the colocated AERONET and MODIS DT retrievals over oceans from all stations in Terra (2000–2014) and Aqua (2002–2014) and applying the same AOD and AE thresholds (AOD > 0.5 and AE < 0.5) to both AERONET and MODIS DT retrievals. We find that the AOD retrieval-based dust detection rate is about 67% to 79%. This is not significantly higher than the existing algorithms, and to implement this methodology, it would require an iterative retrieval to apply a dust model.

In summary, dust detection accuracy from major existing algorithms ranges from 60% to 84% with false detection rate of about 20–30% when compared to dust detection from other sensors, including CALIPSO (Cho et al., 2013; Ciren & Kondragunta, 2014). These studies show that current dust detection algorithms have to make a choice between focusing on heavy dust and ignoring thin dust or accepting large false detection rates in order to identify dust at smaller aerosol loadings. Here we will reevaluate these spectral tests and find a better combination of tests to improve the performance of dust detection for MODIS algorithms.

### 3.2. Evaluation of Dust Tests

One of the major difficulties in developing dust detection algorithms is the lack of ground truth. In the development of Zhao’s algorithm, regions of cloudy, dusty, and smoky were selected to define the threshold from a
handful of granules (Zhao et al., 2010), while others use retrieved aerosol products such as AOD and AE for dust selection (Ciren & Kondragunta, 2014). The former often fails to represent the diversity of dust properties present across different regions. The latter is sensitive to algorithm deficiencies ranging from inaccurate cloud screening to imperfections in the aerosol models used in the retrieval algorithm.

In this study, we start by carefully assembling a training data set that has both dusty granules and granules without dust. To represent different scene types, we picked 19 granules in which the scene types were visually identifiable and which were from different regions and seasons (Table 2). In addition to dusty scenes, we have included several granules with heavy smoke because separating dust from smoke tends to be a major challenge for both dust and smoke detection algorithms. For each granule, we have manually drawn one or two boxes, and we have grouped the pixels (in 1 km resolution) from these boxes into six scene types: dusty, smoky, cloudy, clear over ocean, volcanic ash, and snow/ice surface (Figure 1). The cloud mask from the DT algorithm (based on 3 × 3 pixel variability and 1.38 mm channel brightness) is used to screen out possible cloud contamination in the smoke and dust samples (also excluded from cloud samples). This method ensures that the correct scene type is assigned to each 1 km resolution pixel, independent of the retrieved AOD and AE products, which have the potential to be biased.

We then applied spectral tests, including both single-channel tests and multichannel tests to the carefully selected and screened sample pixels. Figure 2 shows probability distribution functions (PDF) of reflectance or brightness temperature from all collected pixels as a function of scene type, for 14 wavelengths commonly used in single-channel dust tests. As expected, the clear ocean surfaces have the lowest reflectance in all examined shortwave channels. A quick inspection of the other scene types shows that the reflectance of cloud and snow are generally higher than the dust and smoke scenes in the visible and 0.86 μm channels but the PDFs begin to overlap significantly at wavelengths longer than 1 μm. Among the longwave bands examined, the mid-IR wavelength of 3.9 μm—a region of the spectrum where the brightness temperature signal is dominated by the temperature of the underlying surface and atmosphere—showed the least ability to distinguish the different scene types. The 1.37 μm channel is often used to detect thin cirrus clouds because strong water vapor absorption in this region of the spectrum masks radiation from the surface and lower level clouds that could complicate the scene (Gao & Kaufman, 1995). The large reflectance seen in this channel for volcanic scenes may be due to rising of volcanic ashes to very high altitudes. The cutoff values at 5% and 95% of cumulated PDFs (figures not shown) are listed in Table 3. These values can be used as initial thresholds for each of the tests.

We have identified 15 tests that combine multiple wavelengths, as differences, ratios, or normalized difference ratios to identify dust. The multichannel tests (Table 4) manipulate the spectral measurements...
to minimize the surface’s impact on the spectral variations (Figure 3). However, none of the individual multichannel tests could distinctively separate dust from all other scene types, especially smoke.

A scatter plot of two tests can generally delineate different scene types better as more spectral signals can be used simultaneously to constrain the scenes. We paid special attention to the two indices used in the NOAA’s dust detection algorithm (Ciren & Kondragunta, 2014), the DAI and NDAI:

$$\text{DAI} = -100 \left[ \log_{10} \left( \frac{R_{0.41}}{R_{0.44}} \right) - \log_{10} \left( \frac{R_{0.41}}{R_{0.44}} \right) \right]$$  \hspace{1cm} (1)

$$\text{NDAI} = -10 \log_{10} \left( \frac{R_{0.41}}{R_{2.13}} \right)$$  \hspace{1cm} (2)

where $R$ is the observed reflectance, and $R'$ refers to the reflectance due to Rayleigh scattering. After careful inspection of all one-test and two-test combinations, we notice that the DAI test which uses the ratio of two deep-blue channels subtract the ratio of reflectance from Rayleigh scattering is less predictive either by itself or combined with other tests than a single deep-blue channel.

However, we find the NDAI to be quite useful when combined with a reflectance test in 0.41 $\mu$m (Figure 4a). The 0.41 $\mu$m channel is selected to take the advantage of the absorption properties of dust in the deep-blue range of the spectrum. This channel has the shortest wavelength of all MODIS channels and separates absorbing dust and smoke from the brighter cloud and snow surface. The NDAI uses the ratio of reflectance at 0.41 and 2.13 $\mu$m channel to make a distinct separation between the smoke and dust as reported in Ciren and Kondragunta (2014). Because the 2.13 $\mu$m channel is very sensitive to particle size (Kaufman et al., 1997) and because dust and smoke are dominated by particles that differ in size by an order of magnitude, reflectance at 2.13 $\mu$m has the most promise of separating these two types of aerosol. Thus, by using both 0.41 and 2.13 $\mu$m, NDAI combines information that should identify aerosol spectral absorption in the
shortwave typical of dust and smoke and then separate the two types of aerosol by size. NDAI alone begins to 
make that separation, although imperfectly. However, we find that a combination of the 0.41 μm reflectance 
and NDAI is able to separate dust from most of the other scene types except some volcanic ash from the 

Figure 2. Probability distribution functions of reflectivity for wavelengths 0.41 to 2.1 μm and brightness temperature of selected MODIS bands that are greater 
than 2.1 μm wavelength and are commonly used in single-band dust tests. The pixels for difference scenes are manually selected from 19 granules over 
ocean. The MODIS band number and wavelength in micrometer (starts with R or BT in parenthesis) are shown along the x axis. The 5% and 95% of PDF 
values are shown in Table 3. Note that the x axis varies.
Table 3
Single-Channel Tests and Cutoff Values at 5% and 95% Accumulated PDF

| MODIS channel | Wavelength | Dusty range       |
|---------------|------------|-------------------|
| M08           | R0.41      | [0.20, 0.29]      |
| M09           | R0.44      | [0.18, 0.29]      |
| M03           | R0.47      | [0.17, 0.29]      |
| M04           | R0.55      | [0.13, 0.34]      |
| M01           | R0.65      | [0.10, 0.39]      |
| M02           | R0.86      | [0.08, 0.44]      |
| M05           | R1.26      | [0.06, 0.42]      |
| M26           | R1.37      | <0.03 for all cases |
| M07           | R2.13      | [0.03, 0.35]      |
| M20           | BT3.7      | [292.5, 314.3]    |
| M21           | BT3.9      | [287.0, 303.2]    |
| M29           | BT8.7      | [279.5, 296.2]    |
| M31           | BT11       | [279.0, 298.4]    |
| M32           | BT12       | [280.1, 298.2]    |

Note. “R” means “reflectance,” and “BT” means brightness temperature.

Table 4
Multichannel Tests and Cutoff Values at 5% and 95% Accumulated PDF

| Test                  | Dusty range               |
|-----------------------|---------------------------|
| 1 BT11-12             | [-1.34, 0.48]             |
| 2 BT11-3.7 or(BT3.9-11) | [-31.5, -6.51]           |
| 3 BT8.7-11            | [-3.16, -0.01]            |
| 4 R0.55/R0.47         | [0.72, 1.17]              |
| 5 R0.65/R0.55         | [0.80, 1.16]              |
| 6 R0.47/R0.65         | [0.63, 1.54]              |
| 7 NDSI snow index (R0.65-R2.13)/(R0.65 + R2.13) | [-0.0, 0.39] |
| 8 NDDI (R2.13-R.47)/(R2.13 + R0.47)       | [-0.64, 0.09]            |
| 9 NDDI (R0.86-R0.65)/(R0.86 + R0.65)       | [-0.12, 0.28]            |
| 10 SNDVI (R0.47-R0.65)/(R0.47 + R0.65)     | [-0.20, 0.20]            |
| 11 DAI (R0.412/R0.440) | [6.24, 14.05]            |
| 12 NDAI (R0.410/R2.110) | [-7.33, 0.77]            |
| 13 B8–7-1 slope (R0.41-R2.13)/(R0.65-R0.41) | [-11.80, 4.33]          |
| 14 SFCDIF (SST-BT11)   | [0.26, 6.5]               |
| 15 STDEV (0.86 μm)     | [-0.02, 0.01]             |

4. Validation of Combined Dust Detection Algorithm
4.1. Sample Granules

The new dust detection algorithm is tested with the training granules as well as over 50 additional visually identifiable dust and smoke granules. In most cases, the algorithm successfully detects regions of dust in the dusty granules while avoiding misidentifying smoke as dust. In the following, we show a few of such examples. Figure 5 shows dust detections for two heavy dust granules. The first granule shows a large heavy dust plume over North Atlantic Ocean blown from West Africa, and the second one shows heavy but narrow stripes of dust plume originated from inland China across the Yellow Sea. Under the RGB images, from left to right, we show the dust flags detected with the Zhao et al. (2010) algorithm implemented within the MODIS cloud mask (MxD35), the “likely dust pixels” based on the MODIS DT aerosol retrieval (MxD04) with thresholds set at AOD > 0.5 and AE < 0.6, and the dust detection flags using the new algorithm. In both cases the new dust detection algorithm detects more dust area than either the Zhao et al. (2010) algorithm or the AOD and AE-based dust identification.

To evaluate and visualize the dust detection globally, we plotted a global map of dust counts in 0.4° × 0.4° grid boxes summed up from Terra and Aqua for a single day on 21 June 2020 amid a historic heavy dust event of West Africa dust transported across the Atlantic Ocean to reach the middle of the Atlantic Ocean, which is mixed with dust in the bottom right side of Figure 4a. The NDAI is not able to separate volcanic ash because of their large particle sizes, and the reflectance at 0.41 μm for the thin volcanic ash could be comparable to dust. In Figure 4b, the BTD between 8.7 and 11 μm effectively removes these volcanic ash pixels from dust due to absorption of SO2 in the 8.7 μm channel.

In addition to these tests, we also include a spatial variability test in 0.86 μm and reflectance ratio tests in three visible channels (R0.47/R0.65, R0.65/R0.55, and R0.55/R0.47) for initial cloud screening and identifying some particularly heavy dust cases. Our final algorithm combines dust signatures from deep-blue, VIS, NIR, SWIR, and TIR spectral regions as follows:

\[ 9 - \text{pixelstd}(R0.86) < 0.02; \]
\[ 0.06 < R0.41 < 0.35; \]
\[ \frac{R0.47}{R0.65} < 0.9 \Rightarrow \text{dust}; \]
\[ \text{if } R0.47 < R0.65 \leq 0.2 \text{ then} \]
\[ \frac{R0.65}{R0.55} \geq 1.15 \text{ and } \frac{R0.55}{R0.47} \geq 1.15 \Rightarrow \text{dust}; \]
\[ \text{NDAI} > -2.8 \text{ or} \]
\[ -10 < \text{NDAI} < -2.8 \text{ and } -3.5 < \text{BTD} 8.6 - 11 < 1.0 \Rightarrow \text{dust}; \]
We notice that the new dust algorithm captures the dust event across the Atlantic Ocean in the 0°–30°N belt. In addition, it captures dust over the Persian Gulf and Arabian Sea. Elsewhere, the globe is dust-free. The DT retrieval captures the dust event in the Atlantic Ocean but

Figure 3. Probability distribution functions of multiband test results over various scenes collected from 19 granules over ocean. The definitions of the tests and the 5% and 95% of PDF values are shown in Table 4. The references to the tests can be found in Table 1. Note that the scales of axes vary.
misses the dust in the Arabian Sea. The MOD35 dust flag captures a much narrower belt of dusty area across the Atlantic but misses the Arabian dust. In addition, it misidentifies a lot of pixels in the Southern Ocean near 60°S as dust.

4.2. AERONET Dust Pixels

For a more quantitative evaluation of the new dust detection algorithm, we compare with AERONET. The dust detection algorithm is applied to ocean MODIS pixels collocated spatially and temporally with AERONET measurements, as described in section 2. One year of data is analyzed, 2011, which consists of 44,900 and 45,551 10-km pixels from Aqua-AERONET and Terra-AERONET collocations, respectively. The collocation uses the 10-km MxD04 output, but the dust detection algorithm uses reflectance and brightness temperature inputs at 1-km resolution. Therefore, for each 10-km aerosol retrieval pixel, we go back to the MxD02 in order to input the corresponding 10 × 10 1-km L1B reflectance and BT data and apply the dust detection tests to each of these 1-km pixels. We consider the entire 10-km retrieval pixel as dusty if at least three 1-km pixels are identified as dusty by the new dust detection algorithm.

Thresholds have to be set to determine dust in the AERONET observations. Because we want to understand how our dust detection algorithm works across a range of aerosol loadings, unlike previous validations of such algorithms, we introduce a set of dynamic thresholds for AERONET pixels from weakest to strongest loadings:

\[
\begin{align*}
\text{AOD} & \geq \begin{cases} 0.3 &; 0.4 &; 0.5 &; 0.6 &; 0.7 &; 0.8 \\
\text{AE} & \leq \begin{cases} 0.8 &; 0.7 &; 0.6 &; 0.5 &; 0.4 &; 0.4 
\end{cases}
\end{cases}
\end{align*}
\]

As the aerosol loading increases, we demand AE to decrease for the observation or scene to be declared dusty. This assumes the background aerosol to consist of more fine mode aerosol and increasing aerosol loading is due to more coarse mode dust.

To provide more quantitative matchup statistics, we computed the accuracy, probability of correct detection (POCD) and probability of false detection rate (POFD) assuming AERONET dust detection as truth. Successful retrievals consist of TP (true positive) and TN (true negative) cases, in which both algorithms identify the pixel as dusty and no dust, respectively, and unsuccessful retrievals consist of FN (false negative) and FP (false positive)—where the new algorithm identifies a pixel as no dust and dust respectively, opposite to what AERONET defines.

\[\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \times 100\%\]  \hspace{1cm} (3)

\[\text{POCD} = \frac{TP}{TP + FN} \times 100\%\]  \hspace{1cm} (4)

\[\text{POFD} = \frac{FP}{TN + FP} \times 100\%\]  \hspace{1cm} (5)

The POCD and POFD here depend on the AERONET dust criteria (Figures 8a and 8c). For example, if a weak criterion is used, that is, AOD > 0.3 and AE < 0.8, more dusty pixels would be identified by AERONET, and the new dust detection reports a low 27% and 30% of POCD from collocated Aqua and Terra data set, respectively. If a strong criterion is used, that is, AERONET AOD > 0.6 and AE < 0.5, the POCD from the new algorithm is more than 90% and 82% for Aqua and Terra, respectively. For a commonly used threshold criterion with AOD > 0.5 and AE < 0.6 (Ciren & Kondragunta, 2014), POCD is about 70%.

Figure 4. Scatter plots of NDAI with (a) reflectance at 0.41 μm and (b) brightness temperature difference at 8.7 and 11 μm (BT8–BT11) for pixels collected from 19 images. Pixels from different scenes, that is, dust, smoke, snow, cloud, volcanic ash, and clear ocean are indicated using different colors. The blue lines indicate threshold values for the respective tests.
Figure 5. The RGB images of two heavy dusty granules (top row) and dust detections from MYD35 dust flag (bottom: first and fourth panels), AOD and AE retrievals from DT algorithm (bottom: second and fifth panels), and new dust detection scheme (bottom: third and sixth panels) shown below each of the RGB images. The white, blue, and yellow colors represent no-test, not-dusty pixels, and dusty pixels, respectively.

Figure 6. The RGB images of a smoke granule over South Indian Ocean (top left) and a volcanic ash granule over North Atlantic Ocean (top right) and corresponding dust detections from MOD35 dust flag (bottom: first and fourth panels), AOD and AE retrievals from DT algorithm (bottom: second and fifth panels), and new dust detection scheme (bottom: third and sixth panels) shown below each of the RGB images. The white, blue, and yellow colors represent no-test, not-dusty pixels, and dusty pixels, respectively.
The POFD in all cases are low, varying from 0.6% to 1.3% from weakest to strongest AERONET criteria due to the large number of TN pixels (Figures 8b and 8d). For comparison, we plotted POCD and POFD if an alternative dust detection method is used with DT-retrieved AOD and AE (i.e., AOD ≥ 0.5 and AE < 0.6). The new algorithm detects 1.5 to 3 times more dusty pixels with only an insignificant increase in false positives than would the old standard DT algorithm as the first step in an iterative procedure.

4.3. Dust Validation With CALIPSO Aerosol Layer Type

The aerosol layer feature from CALIOP has been used as benchmark for many dust detection algorithms (Ciren & Kondragunta, 2014). Here we used a 5-km CALIOP aerosol layer product collocated with a
MODIS-Aqua product from January, April, July, and October 2007. Only pixels with no cloud layers are selected. Again, the new algorithm is applied to 10 × 10 1-km pixels centered at the CALIOP pixel. The MODIS 10-km pixel is defined as dusty if more than three 1-km pixels are classified as dusty. The CALIOP aerosol layer has up to eight aerosol layers, and dust-related aerosol layers can be denoted as “dust,” “polluted dust,” or “marine dust.” For a CALIOP horizontal pixel to be classified as dusty in a total column sense for comparison with MODIS, we require the AOD from 532 nm CALIOP backscattering AOD retrieval to be greater than 0.3 and vary the number of required pure dust layers. The dust detection validation statistics are computed as a function of the number of required dust layers. We did not include marine dust and polluted dust because optical properties of these dust are different than pure dust (in the CALIPSO detection algorithm).

Figure 9 shows the total dusty pixel counts in the 4 months in 1° × 1° grid boxes when requiring different number of minimum dust layers in the CALIOP data: for a minimum of one dust layer (Figure 9a) or three dust layers (Figure 9b). The corresponding MODIS dusty pixel counts from the new dust detection algorithm is shown in Figure 9c. Requiring only one dust layer leads to many more identified dusty pixels than requiring three or more dust layers. In fact, CALIOP 1-dust layer detections could appear anywhere on the globe, unless also accompanied by backscatter AOD restrictions (figure not shown). Hence, requiring more dust layers is necessary to guarantee enough dust in the column to merit a revised MODIS retrieval. The new dust algorithm shows similar regional distributions as the three-dust layer case, albeit the total number is still less than the three-dust layer case.

Table 5 shows the match metrics for dusty pixels defined using different number of dust layers, respectively. With one dust layer as the dusty criteria for CALIOP, the new algorithm’s POCD is only 30.7%. As the

![Figure 8](https://example.com/f8.png)

**Figure 8.** Comparisons of new dust detection results with dust identified with pairs of AERONET AOD (0.3, 0.4, 0.5, 0.6, 0.7, 0.8) and corresponding AE at (0.8, 0.7, 0.6, 0.5, 0.4, 0.3) thresholds. (a and c) Positive detection rates and (b and d) false detection rates for Aqua-AERONET and Terra-AERONET collocated pixels in 2011, respectively. The orange and blue lines show dust detection using the new algorithm and using DT-retrieved AOD and AE thresholds (AOD > 0.5, AE < 0.6, FMF < 0.3), respectively. The dotted lines show total AERONET dusty pixels in (a) and (c) and total nondusty pixels in (b) and (d), respectively.
number of dust layers increases, POCD increases. The POCD is 40.2% and 74.6% for three–dust layer and five–dust layer criteria, respectively. In all cases, the POFD is less than 1%. Since our purpose of dust detection is to identify pixels for the aerosol retrieval algorithm to confidently assign a nonspherical dust model, our new dust algorithm serves this purpose. It captures the heavy dusty pixels, while the false classification rate is extremely low.

5. Global Dusty Pixel Distribution

The dust detection algorithm is applied globally to Aqua MODIS from 12 April to 11 May 2011 (Figure 10) and 1 to 31 July 2011 (Figure 11). The two periods are selected to capture dust prevalence in northwest Asia in April (spread over northwest Pacific; Yu et al., 2012) and the heaviest period of Africa dust occurring in

Figure 9. Dust counts at 1 × 1° grids based on (a) one CALIOP dust layer, (b) three CALIOP dust layers, and (c) new dust detection algorithm for MODIS-Aqua and CALIOP collocated noncloudy pixels in January, April, July, and October 2007.
For July 2011, we notice that the new dust algorithm detects more dust pixels over the subtropical North Atlantic, Mediterranean, Persian Gulf, and especially the Arabian Sea, but fewer dust pixels off East Asia. This appears to match the expected seasonal variation of dust events in these regions (Voss & Evan, 2020). Compared with dust detection from the MxD35 dust flag and the AOD-AE-based dust flag, the new dust detection algorithm captures more of the heavy dusty pixels and reduces false dust detection in the southern oceans. These results are qualitatively similar to the nonspherical AOD fraction from the Multi-angle Imaging SpectroRadiometer (MISR) retrievals for high AOD pixels (Kalashnikova et al., 2013).

We also compared NOAA's Aerosol Detection Product (ADP) (NOAA ATBD, 2020) which implements both Zhao et al. (2010) algorithm and Ciren and Kondragunta (2014) with the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument in July 2018. We find that this algorithm detects much more dust than the other three methods (see supporting information). This aggressive identification of dust would be unsuitable as a prestep for the DT algorithm, as we want to limit the new dust retrieval path in the algorithm to pixels with significantly heavy loading of dust.

### 6. Summary and Discussion

The DT aerosol retrieval is an operational algorithm of the MODIS instruments that retrieves spectral AOD over land and ocean. Over the ocean, the DT algorithm is known to produce biased retrievals of AOD, AE, and FMF, in pixels containing significant dust aerosol because the current version of DT-O does not have an aerosol model capable of faithfully representing these nonspherical dust particles. In this work, we designed and evaluated a two-step dust aerosol retrieval strategy in which we first detect dust pixels and then utilize a new nonspherical dust model in the retrieval of the detected dusty pixels. Here, in Part 1 of the series, we reported on a dust detection algorithm that combines near-UV (deep blue), visible, and TIR wavelength spectral tests based on a survey of existing dust detection algorithms.

The new dust detection algorithm was tested extensively with manually selected dusty granules. Quantitative evaluation of the dust detection algorithm is conducted with collocated AERONET-MODIS detections as well as CALIPSO-MODIS collocations. Instead of using one set of arbitrary threshold criteria, we used progressively changing criteria from weakest to strongest aerosol loading so that the full nature of the dust detection algorithm could be evaluated, from detecting weakly to heavy dust situations. From comparison with both AERONET and CALIOP products, we estimate the new dust detection algorithm detects about 30% of dusty pixels in weak aerosol loading and above 80% of heavy dust pixels. Compared with the dust flag currently implemented inMxD35, and a dust classification scheme based on commonly used thresholds with AOD and AE, the new dust detection algorithm finds more dusty pixels with much fewer false dust detections over high-latitude oceans.

We should point out that the dust detection algorithm developed in this work is not comprehensive due to the extreme complexity of dust's varying physical sizes and chemical compositions in any given region and time. Even though our searching for dust detection tests is guided by physical principles, our method still relies on manually tuning the thresholds which is very difficult for decision trees that involve many layers of nonlinear processes. We expect that a machine learning algorithm might be able to determine better

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**Table 5**

![Table 5](image)

| No. of CALIPSO pure dust layers | No. of CALIPSO dusty pixels | Accuracy | POCID | POFD |
|---|---|---|---|---|
| 1 | 23,458 | 98.6 | 30.7 | 0.2 |
| 2 | 16,889 | 98.9 | 34.7 | 0.3 |
| 3 | 7,018 | 99.2 | 40.2 | 0.5 |
| 4 | 1,708 | 99.3 | 50.3 | 0.7 |
| 5 | 327 | 99.3 | 74.6 | 0.7 |
| 6 | 65 | 99.3 | 96.9 | 0.7 |
| 7 | 5 | 99.3 | 100.0 | 0.7 |

*Note: Total number of noncloudy pixels based on CALIOP is 1,261,460.*

July (Huang et al., 2010). Figure 9 shows that MxD35 dust flag captures many dusty pixels in the northwest Pacific and a small amount of the dusty pixels in North Atlantic off West Africa. But there are a lot of misidentified dusty pixels in the high-latitude Southern Ocean and North Atlantic. Using the DT-retrieved AOD and AE values for dust identification identifies only a few dusty pixels in subtropical North Atlantic, Mediterranean, Persian Gulf, and northwest Pacific regions. The new dust algorithm returns more dusty pixels across the North Atlantic, Mediterranean, Persian Gulf, and northwest Pacific. The small number of dusty pixels across the North Pacific may be transported dust from East Asia. Interestingly, all detection algorithms find dusty pixels in the North Atlantic off New England. With no obvious sources of dust, this is likely a case where turbid water and/or fog may be causing false dust detection.
Although Terra and Aqua will be out of orbit in a few years after providing nearly two decades of high-quality observations, the DT algorithms have recently been ported to the VIIRS instruments onboard thresholds and an improved decision procedure (Wang et al., 2020). Such work is underway; however, it is guided by the knowledge accumulated through physical-based experiment and discovery. The impact of the dust detection scheme developed and reported here on aerosol retrievals in the DT algorithm will be explored in Part 2 of the series as we describe the development and testing of new dust aerosol models for the algorithm (Zhou et al., 2020).

Figure 10. Total number of dusty 10-km pixels from Aqua in 1 × 1° grids during 12 April to 11 May 2011 based on (a) MYD35 dust flag, (b) DT retrievals (AOD ≥ 0.5, AE1 < 0.6, FMF < 0.3), and (c) new dust detection algorithm.

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the Suomi-NPP because of their similar orbital and spectral characteristics as MODIS (Sawyer et al., 2020). In addition, the DT algorithm is being adapted to the next-generation geostationary satellites such as the Advanced Baseline Imager (ABI) on GOES-East and GOES-West and the Advanced Himawari Imager (AHI) on Himawari (Gupta et al., 2019). The dust detection algorithm developed for MODIS would require slight adjustments of thresholds for the VIIRS instrument because of its slightly different spatial resolution and spectral channels than the MODIS and possibly more substantial adjustments for the ABI and AHI instruments because of their lack of deep-blue channels. It is important to implement a proper nonspherical dust model in the DT-O retrieval algorithm to provide better quality dusty retrievals for both climate studies and air quality monitoring.

Figure 11. Total number of dusty 10-km pixels from Aqua in 1 × 1° grids from 1–31 July 2011 based on (a) MYD35 dust flag, (b) DT retrievals (AOD ≥ 0.5, AE1 < 0.6, FMF < 0.3), and (c) new dust detection algorithm.
Data Availability Statement

MODIS level 1 (MxD02) and level 2 (MxD04, MxD35) data are available from NASA DAAC. AERONET products can be obtained from AERONET website (https://aeronet.gsfc.nasa.gov). The CALIPSO Level 2 Cloud/Aerosol layer products (version 4) products are publicly available from the Atmospheric Science Data Center (https://eosweb.larc.nasa.gov/).

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