A New Satellite-Based Global Climatology of Dust Aerosol Optical Depth[✉]

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ABSTRACT

By mass, dust is the largest contributor to global aerosol burden, yet long-term observational records of dust, particularly over the ocean, are limited. Here, two nearly global observational datasets of dust aerosol optical depth τ_d are created primarily on the basis of optical measurements of the aerosol column from 1) the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the *Terra* satellite spanning from 2001 to 2018 and 2) the Advanced Very High Resolution Radiometer (AVHRR) from 1981 to 2018. The quality of the new data is assessed by comparison with existing dust datasets that are spatially more limited. Between 2001 and 2018, τ_d decreased over Asia and increased significantly over the Sahara, Middle East, and parts of eastern Europe, with the largest increase found over the Aral Sea where emissive playa surfaces have been exposed. These daily, observational, and nearly global records of dust will allow for improvement in understanding the role of dust in climate variability.

1. Introduction

Aeolian dust makes up the largest mass fraction of the global aerosol burden (Textor et al. 2006) and produces profound impacts on natural (Rosenfeld et al. 2001; Swap et al. 1992; Mahowald 2011; Miller et al. 2004; Ault et al. 2011; Evan et al. 2006; Strong et al. 2018) and anthropological systems (Tong et al. 2017; Griffin 2007; Shao 2008; Mani and Pillai 2010; Ai and Polenske 2008; Brown 2002). A major limiting factor in understanding the global distribution of dust, how it will change in the future, and its complex interactions with Earth's climate, is the limited availability of measurements especially over the ocean (Prospero and Mayol-Bracero 2013). Airborne campaigns have provided measurements for select places and times (Ralph et al. 2016; Formenti et al. 2003; Chen et al. 2011; Formenti et al. 2008; Stith et al. 2009; Ryder et al. 2013; Klaver et al. 2011) and ground-based networks have provided long-term measurements for specific regions (Malm et al. 1994; Prospero and Nees 1986; Prospero 1999; Holben et al. 1998). Most satellite sensors do not isolate the dust contribution to aerosol optical

depth (AOD) at the point of retrieval, so several methods have been proposed and utilized for studying spatial and temporal variations of dust using satellite measurements and models. These methods have mostly used optical properties of the aerosol column related to particle size (Ginoux et al. 2012; Kaufman 2005), color, and single scattering albedo (Ginoux et al. 2012), or have used the ultraviolet (UV) absorptive property of dust for identification (Ginoux 2003). Several studies have used satellite-based products to study dust aerosol optical depth τ_d over either the ocean or land in select locations. Over the Atlantic Ocean, Kaufman (2005) analyzed τ_d using the Moderate Imaging Spectroradiometer (MODIS) retrievals of AOD and Evan and Mukhopadhyay (2010) used a similar method to create a record of τ_d based on retrievals by the Advanced Very High Resolution Radiometer (AVHRR). In addition, Ginoux et al. (2012) used τ_d over bright land surfaces that is based on MODIS Deep Blue AOD to identify dust source regions. Monthly τ_d has also been used in evaluation of the dust emission schemes of global climate models (Pu and Ginoux 2018b).

More recently, studies have used a combination of satellite observations and models to investigate the distribution of dust globally and trends in dust for select regions. Ridley et al. (2016) produced a long-term mean dataset of τ_d between 2004 and 2008 using AOD retrievals from multiple satellite platforms and dust estimates from several global models and Chin et al. (2014) used satellite

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AOD from several sensors alongside the Goddard Chemistry Aerosol Radiation and Transport (GOCART) model to investigate multidecadal regional trends in aerosol species, including dust. These merged approaches have value in allowing for elucidation of aerosol sources and the ability to distinguish anthropogenic from natural dust. However, they are susceptible to model biases in dust emission and transport. Climate models display a large diversity in dust aerosol optical depth and dust emission, mostly underestimating dust emission from major sources, and do not consistently agree with observations (Evan et al. 2014; Huneeus et al. 2011; Pu and Ginoux 2018a; Kok et al. 2017; Kok 2010; Ryder et al. 2018). Therefore, it is valuable to have complementary extensive observational records of dust for comparison.

Here, we expand on the work of Evan and Mukhopadhyay (2010) by using the extended record of satellite retrievals to produce two nearly global τ_d datasets developed using MODIS (2001–18) and AVHRR (1981–2017) at daily and monthly resolution, respectively, with the former dataset extended to cover both land and ocean regions. Although dust transport happens on a temporal scale of days to weeks, the previously mentioned efforts have focused on estimating monthly mean τ_d . This work provides the longest record of observed daily τ_d to date, at a temporal resolution suitable for analysis of daily transport events (daily) and $1^\circ \times 1^\circ$ spatial resolution.

In the next section we describe the data and methods used in the estimation of global τ_d and provide an estimation of the associated uncertainty. Our results in section 3 include identification of climatological seasonal patterns in τ_d , a comparison of our τ_d estimates as derived from two different sensors, and a comparison of the MODIS-derived dataset with preexisting ground-based measurements of dust aerosol from several locations. We then identify regional trends in τ_d for the period of each record.

2. Method

Two datasets of τ_d were created. The first, which hereinafter will be referred to as τ_d^M , is based primarily on AOD (τ) retrievals from the MODIS instrument on the *Terra* platform, with a companion set of estimates created for the same instrument aboard the *Aqua* platform, (both accessed at <https://ladsweb.modaps.eosdis.nasa.gov>) and extends from 2001 to 2018 for the case of *Terra* and 2003 to 2018 for *Aqua*. The τ_d^M includes estimates over both land and water-covered surfaces. The τ_d^A is based on aerosol optical thickness (AOT) retrievals from the AVHRR instruments aboard the NOAA series

of satellites (Heidinger et al. 2014; Zhao et al. 2008, 2002; Zhao and NOAA CDR Program 2017) and covers the period 1981–2018. AVHRR AOT retrievals are not made over land, and thus τ_d^A is an overwater-only product.

a. Datasets used

MODIS level-3 (L3), Collection 6.1 (C061), daily Dark Target AOD is derived from the measured 500-m resolution reflectance from all visible MODIS bands by taking the average of the measured radiance over all scenes that are cloud free and glint free over the ocean within a 10-km grid box and fitting these values to a lookup table. Level-3 MODIS Dark Target AOD is calculated using the quality assurance confidence screened level-2 pixel-level data. MODIS 550-nm fine-mode fraction f is calculated from the ratio of the small-mode AOD to the total AOD. MODIS Collection 6 (C006) AOD over ocean has been shown to have an expected error of $+(0.04 + 10\%)/-(0.02 + 10\%)$ (Levy et al. 2013). For dust-dominated regions, it has been shown that there is a bias of $+5\%$ (Kaufman 2005). There has been no systematic program for evaluation of MODIS f because its definition is somewhat ambiguous, making evaluations against other estimates difficult (Kleidman et al. 2005). At this time, there is no envelope of error for C061 f . However, Collection 5 (C005) f over ocean was found to agree with Aerosol Robotic Network (AERONET) retrieved sky radiance fine-mode fraction within approximately ± 0.20 (Kleidman et al. 2005), and Bréon et al. (2011) found agreement between MODIS ($\tau^{f, \text{MODIS}}$) and AERONET ($\tau^{f, \text{AERONET}}$) fine-mode AOD, as evidenced by a correlation r value of 0.76, root-mean-square error (RMSE) of 0.08, bias of 0.01, and 53% of retrievals within the C005 envelope of error, $\delta\tau = 0.03 + 0.05\tau^{\text{AERONET}}$, which describes a confidence envelope containing 1 standard deviation σ (i.e., 68%) of $\tau^{f, \text{MODIS}}/\tau^{f, \text{AERONET}}$ matchups. In our estimate of the known uncertainty in τ_d , we assume that the C061 f uncertainty has not changed from the C005 values. Although a quality-assured dataset does exist for $\tau^{f, \text{MODIS}}$, we chose to use the standard dataset so as to retain additional coverage.

The equivalent set of estimates for τ_d^M from the *Aqua* platform extends from 2003 to 2018. The *Aqua* platform passes the equator at 1330 local time, whereas *Terra* passes near 1030 local time. AOD from MODIS *Terra* and *Aqua* have been shown to agree very well (Ichoku 2005). However, globally, *Terra* monthly mean AOD over ocean has been shown to be higher than *Aqua* by $+0.015$ (Levy et al. 2018; Remer et al. 2008). This is partially explained by diurnal cycles in cloud fraction (King et al. 2013), which may create differences in sampling between these sensors, and partially explained

by issues with the total infrared radiation measured by *Terra* (Levy et al. 2018). This paper will focus largely on τ_d^M from the *Terra* platform, because it has a longer record. However, we will discuss decadal trends in τ_d^M derived from *Aqua* in section 4a.

Because our τ_d estimate is built upon AOD, it carries with it the known limitations of the sensors from which it is derived. MODIS AOD retrievals are limited to cloud-free pixels, and errors in cloud screening will impact the AOD estimate. The MODIS aerosol cloud mask uses the standard deviation of reflectance in sets of pixels to remove cloudy pixels, which increase spatial variability. Absolute reflectance at 1380 nm and the ratio of reflectances at 1380 and 1240 nm as well as several infrared tests are used for additional screening of thin cirrus. Over ocean, the brightest and darkest 25% of the remaining pixels are arbitrarily removed and the average reflectance in each channel is calculated from the remaining pixels. Over land, the brightest 50% and darkest 30% of pixels are discarded before the averaging step (Remer et al. 2012). While this usually produces a reasonable result, in the case that unscreened clouds remain before the discarding of the brightest and darkest retrievals, this can produce AOD estimates that are biased high (Kahn et al. 2007). It is known that MODIS AOD is biased very positively (high) in the Southern Hemisphere mid-high latitudes over the Southern Ocean because of extensive broken stratocumulus and cirrus cloud contamination (Toth et al. 2013). We have thus limited these datasets to extend from 60°N to 50°S.

Level-2, version 3, AOD and fine-mode fraction from select sites, as will be discussed in section 2b, retrieved from AERONET (Holben et al. 1998, 2001) sunphotometers using the Spectral Deconvolution Algorithm (SDA), version 4.1 (O'Neill 2003; <https://aeronet.gsfc.nasa.gov>) are used to estimate τ_d^M and τ_d^A over the ocean. In the determination of AERONET fine-mode fraction, two spectral modes of AOD are defined on the basis of the premise that the coarse-mode spectral variation is approximately neutral while the derivative of the fine-mode spectral variation is an approximate function of the fine-mode Ångström exponent (O'Neill 2003). From this, the ratio of fine-mode to total AOD is determined at a reference wavelength of 500 nm from a second-order polynomial fit of the natural logarithm of AOD and wavelength applied to each AOD spectrum across six bands. This definition of fine-mode fraction is different from that used in the MODIS dataset and may result in some disagreement. MODIS f has been shown to slightly overestimate the fine-mode fraction in dust or salt dominated regions by 0.1–0.2 relative to AERONET fine-mode fraction as generated from the O'Neill algorithm (Kleidman et al. 2005), which has

the potential to introduce a small positive bias in our estimated τ_d .

MODIS C061 L3 Deep Blue products [AOD, single scattering albedo (SSA), and Ångström exponent (AE); <https://ladsweb.modaps.eosdis.nasa.gov>] were used in the estimation of τ_d^M over land (Hsu et al. 2013). These products use the blue channels of MODIS where surface reflectance is very low. Pixel-level retrievals are averaged over 10 km × 10 km grids, and data are then aggregated into granules. The L3 products are provided at 1° × 1° resolution. SSA at 412 nm and at 660 nm were used in addition to AE, which is inversely proportional to particle size (Ångström 1929). Deep Blue AOD was used as the basis for estimation of τ_d^M over land and is reported to have an expected error of +(0.04 + 10%)/−(0.02 + 10%) (Hsu et al. 2014). The C061 Deep Blue AOD release extended coverage to all nonsnow land surfaces, whereas C005 only included bright land surfaces.

The 630-nm AVHRR AOT climate data record (CDR) (Zhao and NOAA CDR Program 2017; accessed at <https://www.ncei.noaa.gov/data/>) was used in the estimation of τ_d^A (Zhao and NOAA CDR Program 2017; Chan et al. 2013). The CDR was created using the NOAA AVHRR PATMOS-x level-2B product (Zhao et al. 2008, 2002; Zhao and NOAA CDR Program 2017). Although there is no difference between AOD and AOT, we refer to the MODIS data as AOD and the AVHRR data as AOT because this is how each is referenced in their documentation. It combines retrievals from 17 different sensors, and the overpass time and number of observations per day (4–8) varied between sensors. Large data gaps occur for years before 1985. AVHRR AOT was regridded from its native resolution of 0.1° × 0.1° to a resolution of 1° × 1° using inverse distance weighted interpolation. Aerosol retrievals are only available over ocean and require clear-sky conditions (Heidinger et al. 2014). The CDR AVHRR AOT dataset has a systematic error (positive bias) of 0.03 ± 0.006 and a random error of ±0.113 (Zhao and NOAA CDR Program 2017). The error budget of AVHRR AOT CDR is based on AERONET validation. Another product of AVHRR aerosol loading is available, derived using algorithms from modern sensors (Hsu et al. 2017; Sayer et al. 2017), but it is limited to several years. Therefore, we did not use this product.

Daily mean surface wind speed from the second Modern-Era Retrospective Analysis for Research and Applications (MERRA-2) (Gelaro et al. 2017) 1-h time-averaged surface flux assimilation product (accessed at <https://disc.gsfc.nasa.gov/>) was used in the estimation of marine AOD. This was regridded from its native resolution of 0.625° longitude × 0.5° latitude to a resolution of 1° × 1° using bilinear interpolation.

TABLE 1. Summary of variables and data types used in Eqs. (1)–(3). The f_d , f_m , and f_a represent characteristic AERONET fine-mode fractions for dust, marine, and anthropogenic or biomass-burning-dominated AERONET stations, respectively; τ and f represent the total AOD and fine-mode fraction; and τ_m represents the marine aerosol contribution to the total AOD.

Variable	Platform	Instrument	Retrieval wavelength
τ	Terra/NOAA	MODIS/AVHRR	550 or 630 nm
f	Terra	MODIS	—
f_d	AERONET	Sun photometer (O'Neill method)	500 nm
f_m	AERONET	Sun photometer (O'Neill method)	500 nm
f_a	AERONET	Sun photometer (O'Neill method)	50 nm
τ_m	MERRA-2	Parameterized based on surface wind speed	—

MERRA-2 surface wind patterns have been shown to be similar to other datasets, but greater in magnitude in most regions than MERRA and ERA-Interim and weaker in magnitude than NCEP-R2 (Bosilovich et al. 2015). Similar to most reanalysis products, MERRA-2 winds are weaker than 93% of observations considered in Bosilovich et al. (2015).

b. MODIS dust optical depth over ocean

Our method for estimating τ_d^M over ocean surfaces is based on Kaufman (2005). Underlying this method is the assumption that the major contributions to total AOD are anthropogenic and biomass-burning aerosol, marine aerosol, and dust aerosol, and thus one can deduce τ_d by estimating the contributions from the other aerosol types. As anthropogenic and biomass-burning aerosols are generally dominated by submicrometer particles with AE greater than 1 (Dubovik et al. 2002; Schmeisser et al. 2017), f can be used to discriminate these types from the contributions by coarse-mode-dominant aerosol types.

The total aerosol optical depth τ is

$$\tau = \tau_d + \tau_m + \tau_a, \quad (1)$$

where τ_m and τ_a are the marine and anthropogenic or biomass-burning contributions to τ , respectively. Here we have combined the biomass-burning and anthropogenic aerosols for convenience, because they both have a dominant fine mode and will thus be isolated

and removed from τ simultaneously. The fine-mode aerosol optical depth is given by $f\tau$ and can be expressed as a function of the fine-mode optical depth contributions from the individual aerosol species,

$$f\tau = f_d\tau_d + f_m\tau_m + f_a\tau_a, \quad (2)$$

where f , f_d , f_m , and f_a are the total, dust, marine, and anthropogenic or biomass-burning contributions to f , respectively. Equations (1) and (2) can be combined and rearranged to yield τ_d ,

$$\tau_d = \frac{\tau(f_a - f) - \tau_m(f_a - f_m)}{f_a - f_d}. \quad (3)$$

Data sources for each of these variables can be found in Table 1. Characteristic values of f_m , f_a , and f_d were determined using the average of fine-mode fraction from AERONET stations dominated by each aerosol type, weighted by the total τ (Table 2). This weighting was performed for each station according to

$$f = \sum_{i=1}^N f_i^* \text{AOD}_i / \sum_{i=1}^N \text{AOD}_i, \quad (4)$$

where f is f_a , f_d , or f_m . For f_a and f_d , AERONET stations were chosen on the basis of Cazorla et al. (2013). For f_m , marine aerosol-dominated AERONET island stations were selected based on Lehahn et al. (2010) and

TABLE 2. AERONET stations used for calculation of f_a , f_d , and f_m , with the years of data used from each station in this calculation.

Variable	Mean	AERONET stations
f_a	0.79	Alta Floresta (1993–2018), GSFC (1993–2018), Campo Grande (1995), Mongu (1995–2010), Mainz (1997–2018), Abracos Hill (1999–2005), BelTerra (1999–2005), Cordoba CETT (1999–2010), CEILAP BA (1999–2018), Palaiseau (1999–2018), Skukuza Aeroport (2000), UCLA (2000–18), Hamburg (2000–18), Rio Branco (2000–18), Philadelphia (2001), CCNY (2001–18), Cuiaba Miranda (2001–18), Rome Tor Vergata (2001–18), Fresno (2002–12), Billerica (2002–18), Halifax (2002–18), New Delhi (2004–10), Petrolina Sonda (2004–17), Hong Kong PolyU (2005–18), HongKong Hok Tsui (2007–10), Dayton (2008–18), and Hong Kong Sheung (2012–18)
f_d	0.35	Solar Village (1999–2015), Hamim (2000–07), Tamanrasset INM (2006–18), Tamanrasset TMP (2006), and Eilat (2007–18)
f_m	0.34	Midway Island (2001–15), Nauru (1999–2013), Amsterdam Island (2002–18), Crozet Island (2003–13), ARM Graciosa (2013–18), and American Samoa (2014–17)

FIG. 1. Joint probability distribution of MODIS *Terra* (a) AOD, (b) coarse-mode AOD, and (c) fine-mode AOD binned by daily mean MERRA-2 wind speed in the southern equatorial Pacific (0° – 25° S, 178° – 130° W) from 2001 to 2017. The color contours indicate the percent of total pixels falling within each wind speed and AOD bin. The linear parameterization used to estimate coarse-mode AOD from wind speed ($\tau_{m,c} = 0.008$) is shown by the white dashed line in (b). The constant fine-mode AOD parameterization ($\tau_{m,f} = 0.05$) is shown by the white dashed line in (c).

Chaubey et al. (2011) and through visual selection of additional remote island sites. MODIS retrievals were not used for determining these coefficients since f is only distinguishable over the ocean with this instrument. This makes it likely that all MODIS f estimates contain some significant contribution from sea spray and as such represents a deviation from the methods of Kaufman (2005).

MARINE AEROSOL CONTRIBUTION

Kaufman (2005) parameterized marine aerosol based on NCEP surface (1000 hPa) wind speed at $2.5^{\circ} \times 2.5^{\circ}$ resolution. This parameterization was based on the relationship between surface wind speed from a National Climatic Data Center meteorological station and an AERONET station on Midway Island from 14 months of data, excluding the dust season (February–May) (Smirnov et al. 2003).

Here we consider that the total marine aerosol optical depth is given by

$$\tau_m = \tau_{m,c} + \tau_{m,f}, \quad (5)$$

where $\tau_{m,c}$ and $\tau_{m,f}$ are the coarse- and fine-mode contributions to marine aerosol. We make the assumption that $\tau_{m,f}$ is weakly dependent on wind speed (Satheesh et al. 2006), and that the dependence of τ_m on surface wind speed is primarily from $\tau_{m,c}$ (Lehahn et al. 2010). We identified a region dominated by marine aerosols (0° – 25° S, 178° – 130° W), and set $\tau_{m,f}$ equal to the long-term MODIS fine-mode aerosol optical depth,

$$\tau_{m,f} = 0.05(\pm 0.03), \quad (6)$$

where ± 0.03 is the standard deviation of the daily MODIS fine-mode aerosol optical depth at 0° – 25° S, 178° – 130° W from 2001 to 2017 (Fig. 1c). Assuming the linear relationship,

$$\tau_{m,c} = \alpha w, \quad (7)$$

where w denotes surface wind speed and it is implied that $\tau_{m,c} = 0$ in the absence of surface winds, the proportionality term α was calculated via regression of MODIS *Terra* coarse-mode AOD onto MERRA-2 surface wind speeds, both interpolated to a $1^{\circ} \times 1^{\circ}$ horizontal resolution, and over the same region used to calculate $\tau_{m,f}$. Via the linear regression (Fig. 1b),

$$\tau_{m,c} = 0.008(\pm 0.0001)w, \quad (8)$$

which is consistent with Lehahn et al. (2010), who found $\tau_{m,c}$ to be linearly related to surface wind speed with a slope of $0.009 \pm 0.002 \text{ m s}^{-1}$. We tested three other parameterizations for marine aerosol and found that this parameterization resulted in the lowest bias (+0.02) and lowest RMSE (0.04) when compared with AERONET AOD at Nauru, a remote island station, from 2001 to 2014 for days on which there were clear-sky measurements from both instruments. These other parameterizations are described in the online supplemental material.

Sea salt aerosol has been parameterized previously using linear (Lehahn et al. 2010; Smirnov et al. 2003;

Mulcahy et al. 2008; Glantz et al. 2009; Huang et al. 2010), power-law (Mulcahy et al. 2008; Glantz et al. 2009), and exponential (Moorthy and Satheesh 2000) relationships to 10-m or surface wind speeds from in situ and remote sensing measurements. It is well known that, to first order, sea salt emission is primarily dependent on wind speed (Jaeglé et al. 2011). However, other factors including sea surface temperature (SST), organic material, vertical mixing, advection, wet and dry deposition, and relative humidity could impact sea salt emission to a lesser extent. The second most commonly used predictor, after wind speed, is SST (Jaeglé et al. 2011; Gong 2003). However, laboratory and in situ investigations of the SST dependence of marine aerosol have had contradictory results, indicating that we do not yet fully understand how temperature impacts SSA (Grythe et al. 2014; Mårtensson et al. 2003; Zábori et al. 2012). Therefore, we have chosen to retain a parameterization that is only based upon surface winds.

c. τ_d^M over land

The τ_d^M over land for the time period between 2001 and 2018 was estimated on the basis of the methods of Ginoux et al. (2012) with minor modifications. Ginoux et al. (2012) used C005 MODIS Deep Blue AOD to identify pixels over land that contained dust by their column optical characteristics including AOD of greater than 0.1, AE of less than 0, SSA at 412 nm of less than 0.95, and SSA at 412 nm that is less than or equal to SSA at 660 nm. The AE criterion selects for pixels with a dominant coarse mode to the aerosol size distribution (Ginoux et al. 2012), which should primarily be dust and marine aerosol (Dubovik et al. 2002). The criterion for SSA at 412 nm is related to absorption of solar radiation in the green channel, characteristic of dust, and is effective at removing influences of marine aerosol. The difference in SSA between 660 and 412 nm is used because an optical property of dust is a positive spectra variation of SSA with wavelength, which manifests as a sharp decrease in absorption from the red (660 nm) to blue (412 nm) channels. This criterion is effective at removing any additional influence of biomass burning, because biomass-burning particles have spectral variation with the opposite slope. If a retrieval met all of these criteria, its Deep Blue AOD contributed to the long-term mean of τ_d at that grid cell. To test the thresholds used in Ginoux et al. (2012), we collected these same data within three overland regions where the aerosol signal is dominated by dust, and one overland region where mineral aerosols are unlikely to be present, and binned the pixels of this data for each location by their optical properties using the time period 2006 to 2010. The boundaries of these

regions were chosen visually, selecting for either desert surface boundaries or for vegetation cover (Fig. S8 in the online supplemental material). The dust-dominated locations included a region over the Sahara Desert (10°–30°E, 19°–30°N) (Fig. 2a), a region over the Arabian Desert (40°–50°E, 23°–35°N) (Fig. 2b), and a region over the Taklamakan Desert (77°–88°E, 36°–40°N) (Fig. 2c). The non-dust-dominated location chosen was over equatorial Africa (10°–32°E, 10°S–5°N) (Fig. 2d).

In all three dust-dominated regions, 97%–100% of pixels meet the criterion for SSA at 412 nm < 0.95; in the region dominated by other aerosol types, fewer than 26% of pixels meet this criterion. Similarly, in each dust-dominated region, more than 99% of pixels meet the criterion of SSA at 412 nm $\geq$ SSA at 660 nm, and only 40% meet this criterion for the nondust region. The criterion used in Ginoux et al. (2012) of AOD greater than 0.1 was not used in the creation of τ_d^M here, because we were concerned that this threshold would systematically bias our results.

Ginoux et al. (2012) used a conservative requirement of AE less than 0 to identify dust. However, the updated algorithm used to create the C006 Deep Blue AE product now limits the valid range of values to $0 \leq \text{AE} \leq 1.8$ (Sayer et al. 2013; Hsu et al. 2013). Therefore, we chose a new threshold that is based on the distribution of AE in our three desert regions. When this threshold was replaced with a criterion of AE less than 1, 90% of pixels in the Sahara Desert region, 91% of pixels in the Arabian Desert region, and 73% of pixels in the Taklamakan Desert region met the new threshold and only 5% met it in the nondust region. The new threshold of 1 we have used here is within the values of AE reported for dust regimes in Dubovik et al. (2002). In summary, daily estimates of τ_d^M over land grid cells are composed of the Deep Blue AOD if that pixel met the following criteria:

- 1) MODIS C061 AE 470–670 nm, which is inversely proportional to particle size, of less than 1,
- 2) MODIS C061 SSA at 412 nm, the ratio of aerosol scattering to extinction coefficients at that wavelength, of less than 0.95, and
- 3) MODIS C061 SSA at 412 nm is less than or equal to SSA at 660 nm.

If a pixel did not meet these criteria, its τ_d was set equal to zero. An analysis of the accuracy of this method, through comparison with AERONET, is presented in the online supplemental materials.

d. τ_d^A (1981–2018)

The τ_d^A over the ocean from 1981 to 2018 was derived similarly to what was previously described for MODIS.

FIG. 2. Histograms of (top) Ångström exponent, (middle) single scattering albedo, and (bottom) ratio of SSA at 412 nm divided by SSA at 660 nm for three characteristically dusty regions [(a) the Sahara Desert (19° – 30° N, 10° – 30° E), (b) the Arabian Desert (23° – 35° N, 40° – 50° E), and (c) the Taklamakan Desert (36° – 40° N, 77° – 88° E)] and one anthropogenic aerosol-dominated region [(d) equatorial Africa (10° S– 5° N, 10° – 32° E)] for the period from 2006 to 2010 for daily C061 L3 MODIS Deep Blue products. Colored brown [in (a)–(c)] or green [in (d)] bars indicate bins that match the criterion used to identify dust for the respective optical property.

However, AOT from AVHRR was used rather than MODIS AOD, and the climatological seasonal mean f from the MODIS period, calculated from the MODIS small-mode 660-nm AOD divided by the total 660-nm AOD, was used in Eq. (3) because there is a spectral dependence of f . Evan and Mukhopadhyay (2010) showed that over the tropical North Atlantic, a dusty region, the seasonal cycle in f is far larger than the interannual variability, such that monthly climatological mean f can be used in place of monthly-mean f without introducing significant biases. Here we also assume that the use of monthly climatological f can be used in place of daily f . We tested this assumption by calculating the τ_d^M using climatological f . The results were similar to τ_d^M calculated using daily f with a bias of 0.00 in the long-term global mean over the ocean for the period 2001–17 (RMSE: 0.03). The characteristic fine-mode fractions, f_m , f_d , and f_{an} , were the same as those used in the calculation of τ_d^M .

Following Evan and Mukhopadhyay (2010), a time series of zonal mean stratospheric aerosol optical thickness τ_s as estimated in Sato et al. (1993) was removed from AVHRR AOT before calculation of τ_d^A for years prior to 1999 and was assumed to be zero in subsequent years. This was done to remove the impact of large volcanic eruptions, including Pinatubo (June 1991) and El Chichón (March and April 1982), on τ_d^A . τ_s was not removed in years following 1999 because there have been no volcanic eruptions of the scale of Pinatubo or El Chichón since 1999. The total column AOT peaks immediately following these major eruptions, but τ_s does not peak until 1–3 months later (Fig. 3). This offset results in a remaining peak in the τ_s -corrected AOT, which leads to a coincident peak in τ_d^A . In our analysis of trends in τ_d^A , we exclude 1982 and 1991 to avoid the impact of these events.

Our resultant global mean time series of τ_d^A exhibits fluctuations in years prior to 1995 that are associated with satellite drift, a known issue with the pre-K, L, and

FIG. 3. Uncorrected global mean time series of AVHRR AOT (τ ; red), AVHRR retrieval solar zenith angle (black), and stratospheric AOD (τ_s ; cyan) from Sato et al. (1993), each from monthly mean with seasonal cycle removed.

M series (KLM) NOAA satellites, which has been investigated with respect to long-term variability in cloud cover (Foster and Heidinger 2013; Norris and Evan 2015). Satellite drift, or orbital decay, results in a progressively later equatorial crossing time. Thus, biases in optical depth retrievals may be due to retrieval errors associated with larger solar zenith angles (Fig. 3), or sampling of the diurnal cycle (Norris and Evan 2015). We remove the signal associated with satellite drift via linear regression, following the methods of Norris and Evan (2015). Consequently, at each location, the resultant τ_d^A values are anomalies relative to the global mean.

3. Results

The primary results of this work are two nearly global, daily, observational datasets of τ_d at a 1° horizontal resolution that can be used for studies of the global dust cycle. The long-term mean global τ_d^M over the ocean was found to be 0.03 ± 0.06 where ± 0.06 is the $\pm 1\sigma$ error estimate. For comparison, Ridley et al. (2016) found global dust AOD at 550 nm to be 0.03 ± 0.005 using in situ and satellite observations combined with global models. The long-term mean global τ_d^M over land was found to be 0.1. The remainder of this section will be used to present a comparison of τ_d^A and τ_d^M (section 3a), verification of τ_d^M against ground-based measurements of dust (section 3b), and a description of seasonal climatological mean τ_d (section 3c).

a. Comparison of τ_d^M and τ_d^A

Globally, monthly mean estimates of τ_d^M and τ_d^A agree well, as evidenced by a high correlation coefficient

between the two data ($r^2 = 0.41$), a linear least squares regression slope near unity [$y = 0.90(\pm 0.001)x$], a low RMSE (0.07), and a low offset (-0.01) (Fig. 4a). Much of the disagreement between the two occurs in locations where there are few days on which both AVHRR and MODIS have retrievals (Fig. 5). This is often the case in latitudes above 30°N and below 30°S as well as in characteristically cloudy regions such as the ITCZ (0° – 10°N), the southeastern Atlantic Ocean (10° – 20°S , 10°W – 10°E), and the southeastern boundary of the Pacific Ocean. In dust-dominated regions, τ_d^M and τ_d^A are very well correlated, but with a slope that is greater than 1. For example, in the tropical North Atlantic, the only ocean region where mean τ_d^M is greater than 0.3 in all seasons (Fig. 10, described in more detail below), they are linearly related with a form $y = 1.21(\pm 0.005)x - 0.03$ ($r^2 = 0.76$, RMSE: 0.08, and offset: -0.00) (Fig. 4b). Monthly mean τ_d^A is offset low (bias: -0.18) relative to τ_d^M for τ_d^M greater than 1. We hypothesize that the low offset in τ_d^A is an artifact of misclassification of optically thick dust layers as clouds in the AVHRR AOT cloud clearing algorithm (X. Zhao 2018, personal communication), although it is also contributed to by the difference wavelengths between MODIS AOD retrievals and AVHRR AOT retrievals (Zhao et al. 2008). To determine boundaries around the potential contribution to the offset by the difference in wavelength of AOD retrieval, we perform a back-of-the-envelope calculation. The largest percentage difference in AOD at each wavelength should occur when the AE is large. We use AERONET 500- and 675-nm AOD at the (dust dominated) Tamanrasset station to calculate the mean and upper and lower quartiles of AE for these wavelengths, using only days that met the criteria used for ground-truth validation of dust (see the online supplemental material). In the absence of a 550–630-nm AE from MODIS, we assume that this 500–675-nm AE from AERONET is similar enough to approximate the influence of wavelength differences on the offset between MODIS and AVHRR. Using the lower-quartile AE at Tamanrasset, 0.12, we find that the wavelength difference would contribute a 1.6% offset with τ_d^M greater than τ_d^A . Using the mean AE at Tamanrasset, we find a potential offset of 3.5%; using the upper quartile, it is 5.8%.

We also calculated the linear least squares best fit between the daily τ_d^M and daily τ_d^A , including only dates and pixels where both sensors retrieved AOD (Fig. 4d). We expect that if the low offset of τ_d^A relative to τ_d^M is contributed to by missing data in regions of optically thick dust, the slope of the regression between these datasets will be significantly less steep for the daily data than for the monthly data in the tropical North Atlantic (Fig. 4d). This is because for the monthly mean, MODIS

FIG. 4. Scatterplots of (a),(b) monthly mean and (c),(d) daily τ_d^M and τ_d^A for (top) 60°S–60°N and (bottom) a region over the tropical Atlantic where dust storms are frequent (5°S–20°N, 20°–30°W) for 2001–17. The solid red lines represent the linear least squares regression, and the corresponding slopes and offsets are indicated in each panel, along with RMSE.

would incorporate high τ_d days that AVHRR “missed.” Indeed, we found that the daily τ_d^M and daily τ_d^A are related by the relationship $y = 0.95(\pm 0.0002)x - 0.01$ ($r^2 = 0.54$, RMSE: 0.13, and offset: -0.01) in the tropical North Atlantic. Globally, daily τ_d^M and daily τ_d^A are related by the relationship $y = 0.70(\pm 0.0003)x + 0.01$ ($r^2 = 0.26$, RMSE: 0.09, and offset: -0.01) (Fig. 4c).

The discrepancy in retrievals over large dust plumes can be easily visualized in the case of 27 June 2014, over the tropical Atlantic (Fig. 6). In this case, τ_d^M indicates an optically thick dust plume, centered near 15°N, 30°W, that has been advected over the tropical Atlantic from the Sahara (Fig. 6a). This particularly strong event allowed for dust to be measured in situ as far as Colombia

(Bedoya et al. 2016). In Fig. 6, grid cells that are missing estimates of τ_d or AOD, or grid cells over land, are masked in gray. For the same day, the τ_d^A (Fig. 6b) is largely missing estimates in the region of optically thick dust. This is a result of missing retrievals of AVHRR AOT (Fig. 6d), which occur due to a combination of sun glint and because of the cloud-screening algorithm classifying optically thick dust as cloud.

b. Comparison with existing datasets

It is informative to compare our τ_d with previously published estimates of atmospheric dust. Here, we compare τ_d^M with two recently published time series of dust concentrations over the western United States

FIG. 5. Pearson correlation coefficient between monthly τ_d^M and monthly τ_d^A from 2001 to 2017 with the seasonal cycle removed. Regions where the correlation is not significant at the 95% confidence level are masked. Hatched areas indicate locations where daily matched observations from AVHRR and MODIS *Terra* are present for fewer than 50% of days in the period 2001–17.

(Tong et al. 2017; Hand et al. 2016) and one over the Caribbean (Prospero and Nees 1986; Prospero et al. 1996). The measurements of dust over the western United States are based on surface concentrations of aerosol species. In Hand et al. (2016), iron from IMPROVE stations was used as a proxy for fine dust concentrations and τ_d^M compares well to these annual mean fine dust concentrations (r value = 0.61; p value < 0.01) (Fig. 7). In Tong et al. (2017) several criteria from ground-based IMPROVE data were used to confirm dust events that had been detected in satellite imagery. The criteria included high PM_{10} and $PM_{2.5}$ concentrations, a low ratio of $PM_{2.5}$ and PM_{10} , high concentrations of crustal elements (SI, CA, K, Fe, and Ti), low concentration of anthropogenic components, and low enrichment factors of pollution elements. Annual mean τ_d^M is strongly correlated with estimates of annual number of dust events

(r value = 0.73; p value < 0.05) from this work. Toth et al. (2014) found that globally, the average correlation between total AOD and AOD integrated from 500 m AGL to the surface was 0.61 over land. For the contiguous United States, this correlation was found to be 0.62, with 0.57 over the western time zone. Therefore, although τ_d is a measure of column integrated aerosol, we still expect surface concentrations to be correlated with column integrated values, especially when averaged over a large region. Interestingly, while an increasing trend in dust was noted for these studies for the period between 2001 and 2015, from these results, the extension of the time series through 2017 indicates that dust has been decreasing since 2011.

We also compared our new climatology of τ_d^M with long-term, independent, ground-based dust measurements of dust taken at Ragged Point, Barbados

FIG. 6. The (a) τ_d^M and (b) MODIS AOD from the *Terra* platform and (c) τ_d^A and (d) AVHRR AOT for 27 Jun 2014. Retrievals and estimates over land and locations where there are missing data are shown in gray.

FIG. 7. Annual mean τ_d^M from land grid points in the southwestern United States within the region shown in the red-outlined box (30° – 42° N, 125° – 95° W) in comparison with number of dust events annually in the southwestern United States as reported in Tong et al. (2017) (green) and dust concentration from IMPROVE sites in the southwestern United States as reported in Hand et al. (2016) (blue). IMPROVE stations used in the Tong et al. (2017) analysis are marked with green stars on the inset map, and stations used in the Hand et al. (2016) analysis are marked with blue stars. There are several overlapping stations. The r value and p value of the correlation between τ_d^M from Terra and each other time series are shown in the figure legend.

(Prospero and Nees 1986; Prospero et al. 1996; Prospero 2014). These measurements are based on ash residue from extracted filters with an adjustment factor based on average crustal abundance of Aluminum in soil dust. These data have a standard error that is approximately constant at $\pm 0.1 \mu\text{g m}^{-3}$ for concentrations less than $1 \mu\text{g m}^{-3}$ and about $\pm 10\%$ for higher concentrations. We found that in addition to matching the seasonal cycle of dust at this location (Fig. 8b), monthly mean τ_d^M over Barbados is positively and statistically significantly correlated (r value = 0.50; p value < 0.01) with monthly mean ground-based dust aerosol measurements when the seasonal cycle is removed from both time series (Fig. 8a). Monthly mean τ_d^A from 1982 to 2013 is also statistically correlated (r value = 0.33) with dust concentrations at

Barbados, and shows the same seasonality there as τ_d^M (Fig. S3 in the online supplemental material).

We also compared our dataset with a monthly time series of dust optical depth (DOD) over Syria as published by Pu and Ginoux (2016) (Fig. 9). Similar to Ginoux et al. (2012), Pu and Ginoux (2016) used MODIS Deep Blue C006 AOD, SSA, and AE to construct DOD, and thus the datasets are not independent. However, Pu and Ginoux (2016) updated their method by interpolating optical properties to a $0.1^{\circ} \times 0.1^{\circ}$ grid and using a threshold of SSA at 470 nm along with an empirical relationship between AE and f to derive coarse DOD. The time series are related with a correlation coefficient of 0.87 (p value < 0.01) and show the same trend of increasing dust over Syria (Fig. 9). We are not aware of another

FIG. 8. (a) Time series of monthly mean ground-based dust aerosol measurements on Barbados (red) in comparison with τ_d^M over Barbados (blue), each with the seasonal cycle removed. (b) Climatological monthly mean, with long-term mean removed, of measurements on Barbados (red) and of τ_d^M over Barbados (blue). The r value and p value for the correlation between these time series are shown in the bottom left-hand corner of (a).

FIG. 9. Time series of monthly mean dust optical depth (brown) in comparison with τ_d^M (blue) over Syria (34° – 36.5° N, 36.5° – 41° E), each with the seasonal cycle removed. The r value and p value for the correlation between these time series are shown in the bottom left-hand corner.

independent estimate of τ_d^A against which we can make a comparison.

c. Seasonal dust AOD

Having shown that this satellite-based climatology of dust appears to reflect changes in the atmospheric concentration of dust, we next summarize some of the broader characteristics of the global dust cycle, starting with seasonality. Maxima in seasonal mean τ_d^M are found over the Sahara and the Arabian Peninsula in austral summer (July–August) (Fig. 10d) and over the Taklamakan and Gobi Deserts during spring (March–May) (Fig. 10c). Aeolian transport from the Sahara toward the Americas is visible during all seasons with a maximum extension westward during the summer (Figs. 10d,h), which is well known (Prospero and Mayol-Bracero 2013; Prospero et al. 1996). Seasonal mean τ_d^A , appears far lower than τ_d^M near to major dust sources in all seasons, due to limited retrievals in regions of optically thick dust as described in the previous section. The spring maximum in dust over Asia can be attributed to the seasonal cycle of the Mongolian cyclonic depression and the related high frequency of springtime cold air outbreaks (Sun et al. 2001; Ge et al. 2014). During this season, dust is transported from the Asian continent over the North Pacific Ocean toward North America at latitudes between 30° and 50° N. It is presumed that this dust is primarily from the Taklimakan Desert as the

local topographical and meteorological conditions allow for it to be entrained to elevations exceeding 5 km while dust from the Gobi Desert is, for the most part, confined closer to the surface (<3 km) (Sun et al. 2001). It has also been shown that some portion of this trans-Pacific dust originates from Africa (Creamean et al. 2013).

Discrepancies between τ_d^M over land and τ_d^M over adjacent ocean are visible in some areas with significant anthropogenic aerosol sources, including the Sahel region of Africa and India during austral autumn and spring (Figs. 10a,c). This may be due to different methods and data sources used for estimating τ_d^M over land and ocean. The method used for τ_d^M over the ocean leads to a continuous range of τ_d^M , whereas the threshold approach used for estimation of τ_d^M over land may prevent these gradients when there is mixing between anthropogenic aerosols and dust aerosol. However, this may also partially be the result of the different algorithms used in the retrieval of AOD over land and ocean (Sayer et al. 2013; Hsu et al. 2013) (Fig. S4 in the online supplemental material). While these unphysical discrepancies could be avoided through spatial interpolation across these boundaries, we have chosen not to do this in order to minimize our assumptions and retain a daily dataset that is directly representative of the satellite observations. At the very least, these results suggest that direct comparison of overland and overwater τ_d may be problematic.

A region of high summertime mean τ_d^M is visible over the North Pacific Ocean near 45° N (Fig. 10d). Summertime trans-Pacific transport of dust has been observed (Yumimoto et al. 2010). However, visual inspection of MODIS Terra corrected reflectance on days when τ_d^M over the western North Pacific was high during summer months indicated the possibility of contamination from biomass burning over Europe and Russia. We compared summer seasonal mean τ_d^M and MERRA-2 organic carbon extinction optical thickness at 550 nm (online supplemental Fig. S5; <https://giovanni.gsfc.nasa.gov/>) and confirmed that summer seasonal mean organic carbon was highest over the western North Pacific in years when summer seasonal mean τ_d^M was highest. This supports the hypothesis that there may be biomass-burning contamination over the western North Pacific during these months. The fine-mode fraction f during these summer high τ_d^M events is approximately 0.57–0.63. In the springtime, most of the high τ_d^M events are associated with fine-mode fractions near 0.50, which is closer to f_d .

In addition, because of extensive low cloud cover this region in the western North Pacific has few retrievals during the summer months. The limited number of retrievals is evident in the number of pixels used in the estimate of MODIS Dark Target AOD during the summer in that region. While greater than 36 pixels are

FIG. 10. Seasonal mean (a)–(d) τ_d^M averaged over the period from 2001 to 2018 and (e)–(h) τ_d^A over the period from 1981 to 2018. The long-term global mean $\tau_d \pm 1\sigma$ uncertainty over the ocean for each season and dataset is featured in the bottom left-hand corner of each panel.

incorporated on average in the equatorial Pacific estimations of MODIS Dark Target AOD, only approximately 26 on average are used in this estimation in parts of the western North Pacific. Long-term seasonal mean τ_d^A appears low in the western North Pacific in all seasons (Figs. 10c–f).

4. Discussion

Having presented two datasets of τ_d derived from satellite observations, we next present regional trends in τ_d (section 4a) and a comparison of τ_d^M with a modern reanalysis dust extinction aerosol optical depth product (section 4b).

a. Trends in τ_d^M

In Fig. 11a we show regional trends in monthly mean τ_d^M from Terra between 2001 and 2018, where the seasonal cycle has been removed. Only trends that are significant at the 95% confidence level are shown. One region that stands out with a large upward trend in dust is the Arabian Peninsula, where values exceed $0.3 (10 \text{ yr})^{-1}$ for the MODIS period. This is consistent with previous

studies that found increasing trends, of smaller magnitude, in τ in this region (Hsu et al. 2012; Alfaro-Contreras et al. 2017; Toth et al. 2016). Parts of the Saharan Desert appear to be getting dustier in τ_d^M from Aqua. However, coastal Northern Africa and the edges of the Sahara display decreasing trends in τ_d^M from Terra (Fig. 11). Our results show a statistically significant decrease in τ_d^M over northern China (approximately 100°E , 40°N), and over southwest Asia (approximately 180°E , 30°N). This is consistent with recent findings by Pandey et al. (2017), who found that premonsoon dust loading decreased between 2000 and 2015. This decrease has been linked to increased rainfall, and resultant wet scavenging and increased soil moisture, and, to a lesser extent, decreased wind strength. The decrease in τ_d^M over northeast Asia may also be the continuation of a documented decreasing trend from the late 1950s through the 1980s in the region due to reduced cyclone frequency (Qian et al. 2002).

Interestingly, the greatest increase in τ_d^M (1.04 units per 10 yr) is seen over the Aral Sea at the intersection of Kazakhstan and Uzbekistan (44.5°N , 59.5°E). This was once the location of one of the world's largest lakes,

FIG. 11. Trend in (a) τ_d^M Terra (2001–18), (b) τ_d^M Aqua (2003–18), and (c) τ_d^M (1981–2018) with the seasonal cycle removed. Only trends that are significant at the 95% confidence level are shown.

spanning over 66 000 km² (Izhitskiy et al. 2016). However, the lake has been drying up since the early 1960s, when irrigation projects diverted the rivers that fed it leaving behind a highly emissive exposed playa (Micklin 1988; Indoitu et al. 2015). The eastern basin of the lake dried up completely in 2014, but the northern parts of the sea remain filled and have largely stabilized. A dramatic increase in τ_d^M is also seen over Razzaza Lake in Iraq, where the shoreline is receding due to diverted irrigation water. The northern-most region of the Caspian Sea, which is also the shallowest portion of the sea, shows a smaller but significant increase in τ_d^M potentially

due to the recession of this body of water over the past two decades (Chen et al. 2017).

τ_d derived from MODIS Aqua (2003–18) displays the same trends of decreasing dust over northeast China and southwest Asia and increasing trends over the Arabian Peninsula (approximately 20°N, 70°E) and central Sahara (approximately 20°N, 10°E) (Fig. 11b). There are some regional changes that are more pronounced in this record, including a statistically significant increase in τ_d over Southern California (approximately 34°N, 119°W). There is also a large increase in dust over Oman (0.20; approximately 20°N, 57°E) that is not present in the τ_d^M

FIG. 12. (a) Monthly MERRA-2 dust extinction aerosol optical thickness at 550 nm and monthly mean τ_d^M over Ragged Point between 2001 and 2013 with the seasonal cycle removed. (b) Annual mean MERRA-2 dust extinction aerosol optical thickness at 500 nm and annual mean τ_d^M over the southwestern United States (red-outlined box) from 2001 to 2016.

derived from *Terra* and a greater increase over Iran than is present in the τ_d^M derived from *Terra*. Differences in regional trends between these two datasets could be due the differences in the length of record, as well as the differences in overpass time for the two satellites from which the datasets are derived as it relates to the daily cycle of dust emission (Heinold et al. 2013; Kocha et al. 2013). *Terra* has a morning orbit while *Aqua* has an afternoon orbit (Ichoku 2005). However, it has been shown that although there is no significant overall trend, the offset between the *Terra* and *Aqua* C6 total AOD records has oscillated direction over time, and its variability has increased (Levy et al. 2018). This is likely to impact the differences in τ_d^M from *Aqua* and *Terra*.

Trends in overwater τ_d , from 1981 to 2018, were also calculated using monthly mean τ_d^M (Fig. 11c). Over these longer time periods, there is a small increasing trend in τ_d^A near the Arabian Peninsula [$0.02 (10\text{ yr})^{-1}$] and a decreasing trend in τ_d^A in the tropical North Atlantic near to the African coast [$0.01 (10\text{ yr})^{-1}$]. The decreasing trend over offshore of northern Africa is consistent with the time series of dust at Cape Verde (16.5°N , 23.04°W) created using a similar method (Evan and Mukhopadhyay 2010), and with another study that utilized satellite and coastal surface measurements (Chin et al. 2014).

We note that Zhao et al. (2013) found a slight positive trend in the CDR AVHRR AOT record that is the result of residual cloud contamination. As such, trends in

the tropical North Atlantic and Arabian Peninsula could be similarly biased.

b. Comparison with a modern reanalysis dust product

To understand whether this observation-based dataset is consistent with a modern reanalysis dust product, we compared τ_d^M with MERRA-2 dust extinction aerosol optical thickness at 550 nm (<https://giovanni.gsfc.nasa.gov/giovanni/>) over two of the regions—Barbados and the southwestern United States—used previously in our comparisons with ground observations (Figs. 7 and 8). Our monthly mean τ_d^M , with the seasonal cycle removed, was significantly correlated at the 99% confidence level (r value = 0.73) to the monthly mean MERRA-2 dust extinction aerosol optical thickness over Barbados (Fig. 12a). However, the annual mean τ_d^M displays greater interannual variability and was much more similar to the ground observational record than the MERRA-2 dust extinction aerosol optical thickness over the southwestern United States (Fig. 12b). Over this location, the MERRA-2 dust record was not statistically significantly correlated (r value = 0.20) with τ_d^M .

5. Conclusions

These global, daily, observation-based datasets of dust aerosol optical depth are rooted in observations of optical characteristics of the aerosol column from *Terra* Moderate resolution Imaging Spectroradiometer and

from the Advanced Very High Resolution Radiometer, but incorporate observations of characteristic fine-mode fraction in dusty, clean marine, and anthropogenically dominated regions from the Aerosol Robotic Network as well as surface wind speed from the second Modern-Era Retrospective Analysis for Research and Applications. As previously mentioned, the long-term mean global τ_d^M over the ocean was found to be 0.03 ± 0.06 . Although there are few measurements of dust aerosol for comparison, τ_d^M over land compares well to ground-based measurements of dust from the Interagency Monitoring of Protected Visual Environments network in the western United States and τ_d^M over ocean compares well to independent ground-based measurements made at Ragged Point.

We had hoped to create a reliable dataset of τ_d^A extending from 1981 to 2018 using AVHRR aerosol optical thickness from the Climate Data Record AOT dataset, but we found that the AVHRR AOT had limited coverage in dusty regions. Comparison of daily AVHRR AOT and MODIS AOD over the tropical Atlantic indicated that this limited coverage is at least partially explained by optically thick dust identified as cloud in the AVHRR cloud masking process. This limited coverage results in a low offset in seasonal and monthly mean τ_d^A when compared with τ_d^M . We found that τ_d^M increased in the central Sahara and the Middle East and decreased over northern China and southwestern Asia between 2001 and 2018. The largest increase in τ_d occurred over the Aral Sea, which has receded, leaving emissive playa surfaces exposed. We found decreasing trends in τ_d^A near Africa in the equatorial Atlantic and increasing trends near the Arabian Peninsula from 1981 to 2018.

In 2011, the *Suomi National Polar-Orbiting Partnership* (SNPP) satellite was launched carrying the Visible Infrared Imaging Radiometer Suite (VIIRS), which is intended to continue the observational records that have been provided by sensors such as MODIS and AVHRR (Sayer et al. 2017). VIIRS has been shown to be capable of identifying aerosol type and partitioning between fine- and coarse-mode aerosol. As such, observational studies that require a shorter record (beginning in 2012) may be able to rely on these products. In addition, Chen et al. (2018) demonstrated that an inversion technique, utilizing the GOES-Chem model, can be applied to certain satellite aerosol optical property retrievals in order to retrieve desert dust. This was applied to one year of satellite-derived aerosol information generated by the General Retrieval of Atmosphere and Surface Properties (GRASP) algorithm from Polarization and Anisotropy of Reflectances for Atmospheric Sciences coupled with Observations from a Lidar (POLDER/PARASOL) retrievals. This technique can provide daily dust at $2^\circ \times 2^\circ$

resolution with uncertainty below 25.8%, but it is computationally costly and has not been applied to longer records of remotely sensed aerosol optical properties.

The current work provides daily τ_d generated from a simple algorithm and observed aerosol data. Previous estimates of τ_d have enhanced our understanding of the global dust cycle and have been a valuable tool for evaluating the performance of global models (Pu and Ginoux 2018a; Evan and Mukhopadhyay 2010; Kaufman 2005; Ginoux et al. 2012). This longer, higher-temporal-resolution record will facilitate additional advances in our understanding of the dust cycle.

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