



Introducing the MISR Level 2 Near Real-Time Aerosol Product

Marcin. L. Witek¹, Michael J. Garay¹, David J. Diner¹, Michael A. Bull¹, Felix C. Seidel¹, Abigail M. Nastan¹, and Earl G. Hansen¹

¹Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Drive,
Pasadena, CA 91109, USA

Abstract

Atmospheric aerosols are an important element of Earth's climate system, and have significant impacts on the environment and on human health. Global aerosol modeling has been increasingly used for operational forecasting and as support to decision making. For example, aerosol analyses and forecasts are routinely used to provide air quality information and alerts in both civilian and military applications. The growing demand for operational aerosol forecasting calls for additional observational data that can be assimilated into models to improve model accuracy and predictive skill. These factors have motivated the development, testing, and release of a new near real-time (NRT) level 2 (L2) aerosol product from the Multi-angle Imaging SpectroRadiometer (MISR) instrument on NASA's Terra platform. The NRT product capitalizes on the unique attributes of the MISR aerosol retrieval approach and product contents, such as reliable aerosol optical depth as well as aerosol microphysical information. Several modifications are described that allow for rapid product generation within a three-hour window following acquisition of the satellite observations. Implications for the product quality and consistency are discussed as compared to the current operational L2 MISR aerosol product. Several ways of implementing additional use-specific retrieval screenings are also highlighted.

© 2021. California Institute of Technology. Government sponsorship acknowledged



1. Introduction

Atmospheric aerosols have for long been recognized to influence the climate, environment, and human health (e.g., IPCC, 2013; Lelieveld et al., 2015; Shindell et al., 2013; Turnock et al., 2020). They also affect satellite remote sensing of important geophysical parameters such as ocean color (e.g., Frouin et al., 2019; Gordon, 1997) or greenhouse gas abundance (Butz et al., 2009; Frankenberg et al., 2012; Houweling et al., 2005). Aerosol particles and their properties have been extensively studied in-situ and remotely: from the ground, in the air, and from space. These observational data vary in spatial and temporal coverage, but usually only offer snapshots of local conditions. Since atmospheric aerosols have a life cycle ranging from hours to days, numerical modeling of their emission, transport, and deposition has filled the coverage gaps and extended our understanding of their global impacts. This has given rise to a number of global aerosol reanalyses (Gelaro et al., 2017; Inness et al., 2013, 2019; Lynch et al., 2016; Rienecker et al., 2011) that provide a long-range, gridded, and internally consistent outlook on aerosol burdens around the world. Furthermore, global aerosol modeling has been increasingly used for operational forecasting (e.g., Xian et al., 2019) and as support to decision making, for example in air quality alerts and in non-civilian applications (Liu et al., 2007).

The growing demand for consistent gridded aerosol products has been driving development and steady improvement of numerical predictions. Still, models suffer from often poorly resolved aerosol emissions and sinks and can be affected by errors in the underlying meteorology. As a result, systematic and sampling-related biases in aerosol fields are often found between model simulations and satellite observations (e.g., Buchard et al., 2015; Colarco et al., 2010; Lamarque et al., 2013; Zhang and Reid, 2009). An effective way to mitigate some of these problems is by assimilating aerosol observations into numerical models (e.g., Bocquet et al., 2015; Fu et al., 2017; Sekiyama et al., 2010; Di Tomaso et al., 2017; Werner et al., 2019; Zhang et al., 2008). Satellite observations of aerosol optical and microphysical properties are inseparable from these data assimilation activities as they offer the necessary data volume, near-global coverage, and frequent repeat cycle. However, an often-considerable latency for generating science-quality “standard” satellite products (8 to 40 hours) renders them unsuitable for operational forecasting. This has led to the development of aerosol products within the time frame required by modeling centers, usually three hours from satellite overpass. A range of near real-time (NRT) products has emerged.

One example of a platform that provides users with NRT satellite products and imagery is NASA's Land, Atmosphere Near real-time Capability for EOS (LANCE) project



63 (<https://earthdata.nasa.gov/earth-observation-data/near-real-time>). A range of instruments
64 deliver various Level 1 (L1) and Level 2 (L2) data products
65 ([https://earthdata.nasa.gov/collaborate/open-data-services-and-software/data-information-](https://earthdata.nasa.gov/collaborate/open-data-services-and-software/data-information-policy/data-levels)
66 [policy/data-levels](https://earthdata.nasa.gov/collaborate/open-data-services-and-software/data-information-policy/data-levels)), including radiances, land surface properties, and atmospheric
67 thermodynamics and composition within three hours from satellite observation. NRT aerosol
68 products are currently available from the Moderate Resolution Imaging Spectroradiometer
69 (MODIS), Ozone Monitoring Instrument (OMI), and Visible Infrared Imaging Radiometer Suite
70 (VIIRS). NASA's Multi-angle Imaging SpectroRadiometer (MISR) currently provides NRT
71 radiance and cloud motion vector products. The purpose of this paper is to introduce a new
72 MISR NRT L2 aerosol product.

73 This paper is organized as follows. Section 2 and 3 provide brief descriptions of the
74 MISR instrument and the data processing sequence, respectively. Section 4 first outlines the
75 cloud identification methods employed in the MISR aerosol algorithm and then describes
76 algorithmic modifications introduced in the NRT processing. Adjustments to cloud and retrieval
77 screening parameters and their implications are discussed. The global distributions of the NRT
78 product are analyzed in Section 5. Section 6 provides a summary.

79

80 **2. MISR instrument and aerosol data product**

81

82 The MISR instrument flies aboard the NASA Earth Observing System (EOS) Terra satellite,
83 launched in December 1999 to a sun-synchronous descending polar orbit, at an orbital altitude
84 of 705 km, an orbital period of 99 minutes, and an equatorial crossing time of 10:30 a.m. local
85 time. MISR makes 14.56 orbits per day with a repetition cycle (revisit) of 16 days. The orbit
86 tracks are georeferenced to a fixed set of 233 ground paths. With a cross-track swath of about
87 380 km, total Earth coverage is obtained every 9 days at the equator and every 2 days at high
88 latitudes.

89 MISR contains nine pushbroom cameras with viewing angles at the Earth's surface
90 ranging from 0° (nadir) to +/- 70.5° oriented along the direction of the flight track. A point on the
91 ground is imaged by all nine cameras in approximately 7 minutes. The cameras make
92 observations of reflected solar radiance in four spectral bands, centered at 446 (blue), 558
93 (green), 672 (red), and 866 (near-infrared) nm. The spatial resolution depends on the camera
94 and wavelength. The red band has a full 275 m resolution in all cameras. The other three
95 spectral channels are averaged onboard to a 1.1 km resolution in global-mode operation (Diner



et al., 1998), with the exception of the nadir camera which preserves the full 275 m resolution in all spectral channels. See <https://misr.jpl.nasa.gov/Mission/> for more details.

MISR employs two processing pathways for aerosol retrievals, one for observations over land (Martonchik et al., 2009), and another for dark water (DW) (Kalashnikova et al., 2013), which applies over deep oceans, seas, and lakes. Previous versions of the MISR aerosol product were extensively validated over the years (e.g., Kahn et al., 2010; Kahn and Gaitley, 2015; Kalashnikova et al., 2013; Shi et al., 2014; Witek et al., 2013) showing high retrieval quality over land and ocean.

The current operational version of the MISR aerosol product, designated as version 23 (V23), was released publicly in June 2018. It introduced multiple algorithmic, data product, and data usability improvements (Garay et al., 2020; Witek et al., 2018a, 2018b). V23 provides aerosol information with a spatial resolution of 4.4 km x 4.4 km packaged in NetCDF-4 format. Initial validation efforts showed that V23 retrievals are more accurate than previous versions, with most pronounced improvements in the DW algorithm (Garay et al., 2020). V23 retrievals over oceans were extensively validated by Witek et al. (2019), indicating excellent agreement with ground-based observations. Other V23 Aerosol Optical Depth (AOD) evaluation efforts show similar results (e.g., Choi et al., 2019; Sayer et al., 2020; Si et al., 2020; Sogacheva et al., 2020). A first regional insight into retrieved particle properties from the MISR V23 aerosol product shows that MISR generally captures the distinct spatial and temporal features of aerosol type in East Asia (Tao et al., 2020). Furthermore, V23 has greatly improved the quality of reported AOD uncertainties, which now realistically represent retrieval errors (Sayer et al., 2020; Witek et al., 2019). This is especially relevant as pixel-level retrieval uncertainties are very important for satellite data assimilation, which is being increasingly used in aerosol modeling studies (Lynch et al., 2016; Shi et al., 2011, 2013; Zhang and Reid, 2010). MISR data and related documentation can be obtained from: <https://asdc.larc.nasa.gov/project/MISR>.

121

122 3. NRT latency and data description

123

MISR currently provides several L1 and L2 near real-time (NRT) radiance and cloud motion vector products (<https://earthdata.nasa.gov/earth-observation-data/near-real-time/download-nrt-data/misr-nrt>). All MISR NRT processing is based on Level 0 data downlinked in observational sessions. These session-based files, representing portions of a single MISR orbit, usually cover between 10 to 50 minutes of observations, as compared to the full orbit period of 98.9 minutes.



129 This session-based processing is necessary to allow for the fast product delivery required for
130 NRT applications.

131 The new NRT L2 aerosol product file content, described in Data Product Specification
132 (ref), is equivalent to the standard aerosol product (Garay et al., 2020). The NRT L2 aerosol
133 product file name convention is:
134 MISR_AM1_AS_AEROSOL_T{yyyymmddHHMMSS}_P{ppp}_O{oooooo}_F13_0023.nc, where
135 'yyyy', 'mm', and 'dd' are the year, month, and day, and 'HH', 'MM' and 'SS' are the hour,
136 minute, and seconds, respectively. Furthermore, {ppp} is the three-digit path identifier (between
137 001 and 233) and {oooooo} is the six-digit orbit number. The NRT L2 aerosol product files are
138 available for download within three hours of acquisition at NASA's Atmospheric Science Data
139 Center (ASDC) (<https://asdc.larc.nasa.gov/project/MISR>).

140 For clarity, it is important to distinguish between the MISR L2 NRT, FIRSTLOOK, and
141 standard aerosol products (see Figure 1). NRT is generated within a three-hour time interval
142 after acquisition and uses the same ancillary inputs as FIRSTLOOK. These include the monthly
143 gridded (1.0 degree) snow/ice mask and surface wind speed from the Terrestrial Atmospheric
144 and Surface Climatology (TASC) database and the seasonal Radiometric Camera-by-camera
145 Threshold Dataset (RCTD) (Diner et al., 1999a). Both NRT and FIRSTLOOK utilize TASC and
146 RCTD datasets from the current month/season in the prior year. The FIRSTLOOK product is
147 generated within two days from acquisition and includes cloud classification parameters
148 obtained from the L1 and L2 cloud products. The standard aerosol product is available after final
149 processing is performed on a seasonal basis and within three months past the end of the
150 season, which results in a 3–6-month latency. The final processing utilizes the most recent
151 snow/ice and wind speed data.

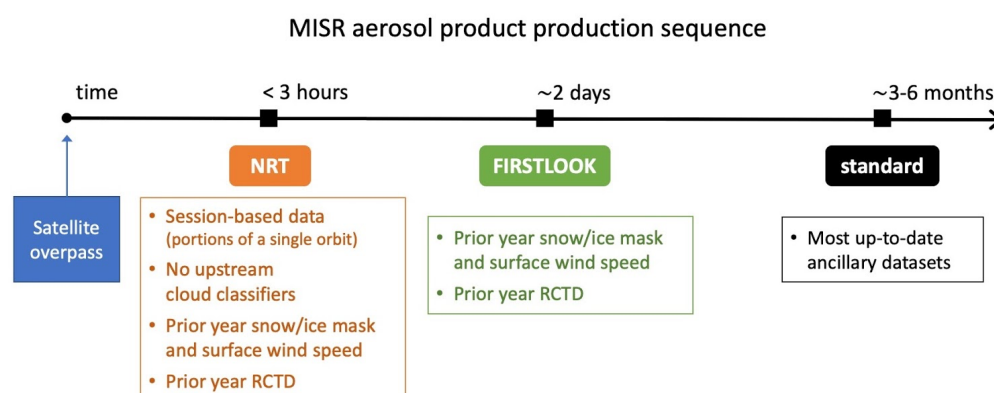


Figure 1 Schematic showing MISR aerosol product delivery timeline. Snow/ice mask and surface wind speed data are monthly averages. RCTD stands for Radiometric Camera-by-camera Threshold Dataset. MISR final production (standard product) is processed on a seasonal cycle and is often delayed one to three months past the end of each season, which results in up to 6-month latency.

4. NRT aerosol product cloud screening

4.1. Cloud identification

Identification of cloudy pixels is a critical element of all satellite aerosol remote sensing algorithms. MISR employs several cloud identification strategies which can be loosely split into two groups: The first group relies on cloud classifiers previously generated with MISR Level 2 Cloud Detection and Classification algorithm (Diner et al., 1999b), and the second group includes build-in tests that are internal to the aerosol retrieval algorithm (Diner et al., 2008).

4.1.1. Upstream cloud classifiers

The operational MISR aerosol algorithm relies on a range of external input datasets that are either static—for example, a monthly wind speed climatology—or that need to be generated prior to aerosol retrievals in upstream processing. A notable example of such external inputs to the standard and FIRSTLOOK algorithms are cloud classification parameters obtained from the MISR L2 cloud product. An important implication of this dependency is that aerosol processing needs to wait for the cloud product to be generated, creating a time lag that is prohibitive for NRT applications. Typically, the L2 cloud product is generated within about 18 hours of



177 overpass, and the MISR L2 FIRSTLOOK aerosol processing is completed within about 2 days.
 178 In order to produce an L2 aerosol product within an about three-hour time frame, the algorithm
 179 needs to operate without the upstream cloud classifiers.

180 Two specific L2 cloud classification parameters utilized in aerosol processing are the
 181 MISR Stereoscopically-Derived Cloud Mask (SDCM) and the Angular Signature Cloud Mask
 182 (ASCM) (Diner et al., 1999b; Girolamo and Davies, 1994). In addition to these L2 products, the
 183 Radiometric Camera-by-camera Cloud Mask (RCCM) (Diner et al., 1999a; Girolamo and
 184 Davies, 1995) retrieved in L1B processing is also employed. All three parameters are reported
 185 at 1.1 km x 1.1 km resolution. It should be noted that RCCM also serves as an input to the
 186 algorithm that generates SDCM and ASCM, indicating that these parameters are not
 187 independent.

188 In the standard aerosol algorithm, the RCCM, SDCM, and ASCM cloud masks are used
 189 together to determine whether a particular 1.1 km x 1.1 km subregion is clear or cloudy. The
 190 implication is that if any of the 9 MISR cameras is designated as cloudy in a subregion, this
 191 subregion is excluded from aerosol retrieval. The clear/cloudy decision logic depends on the
 192 underlying surface type, assigned into three categories: land, water, and snow/ice. Generally, a
 193 “clear” outcome is favored over the two most frequently used surface types, land and water,
 194 assigning a subregion as cloudy only if the RCCM and SDCM masks indicate a cloud. The logic
 195 is considerably more conservative over snow/ice surfaces due to difficulties in distinguishing
 196 clouds from the underlying bright features. Details of the cloud mask decision logic over different
 197 surface types can be found in Diner et al. (2008).

198 Analyzing three months of V23 L2 aerosol product (March, April, May, 2020) indicates
 199 that the cloud masks along with the brightness test (see 4.1.2) lead to screening of about 50%
 200 of retrievals. As such, they have the largest impact on identifying and removing pixels where
 201 clouds might be present. These masks and decision pathways, however, have their deficiencies
 202 and additional checks were put in place to further decrease the frequency of cloud-
 203 contaminated aerosol retrievals.

204

205 **4.1.2. Build-in cloud detection methods**

206

207 In addition to the cloud masks retrieved in the L1B processing (RCCM) and from the L2 Cloud
 208 Detection and Classification algorithm (SDCM, ASCM), the MISR aerosol retrieval algorithm
 209 relies on three internal tests to further identify cloudy pixels that might have escaped earlier
 210 detection. These are (1) the *brightness test*, (2) the *angle-to-angle smoothness test*, and (3) the



211 *angle-to-angle correlation test*. Details of these tests can be found in Diner et al. (2008) or Witek
 212 et al. (2013), but a short summary is provided here for completeness.

213 The brightness test is employed to identify clouds that lacked sufficient texture to be
 214 picked up by SDCM. For each surface type a fixed threshold is adopted on measured
 215 bidirectional reflectance factors (BRFs), and when exceeded in all spectral bands for at least
 216 one camera, it renders a subregion unsuitable for aerosol retrieval. The thresholds are set to
 217 1.0, 0.5, and 0.5 for snow/ice, land, and water surfaces, respectively. The value of 1.0 means
 218 that the brightness test is effectively turned off over snow/ice. Furthermore, the brightness test
 219 does not override subregions that were identified as clear by RCCM.

220 The angular smoothness test checks for unusually large variations in the measured
 221 equivalent reflectances as a function of camera angle, the premise being that in the absence of
 222 artifacts or subpixel clouds, the measured radiance should change smoothly from camera to
 223 camera. The test is achieved by fitting a polynomial to equivalent reflectances, separately for aft
 224 (+nadir) and forward (+nadir) cameras and each spectral band, and checking if the goodness of
 225 fit metric (definition in Diner et al., 2008) exceeds a threshold. If in at least one case the test
 226 fails, the subregion is eliminated.

227 Finally, the angle-to-angle correlation test also investigates radiance smoothness and
 228 correlation between camera angles, which makes it conceptually similar to the angular
 229 smoothness test, but instead utilizes high-resolution information from the red spectral band. It
 230 uses 4 x 4 arrays of the 275m spatial resolution red band equivalent reflectances in each 1.1 km
 231 x 1.1 km subregion. The test then evaluates spatial variability within the 4 x 4 array for each
 232 camera and compares it to a variability within a camera-average template. Variances,
 233 covariances, and normalized cross-correlations are calculated (see Diner et al., (2008) for
 234 details). If the variability within a camera deviates considerably from the average, this camera
 235 might have sub-pixel clouds or other contaminants, and as a result the subregion is excluded
 236 from aerosol retrievals.

237 In the three months of data analyzed in this study (March, April, May 2020), the relative
 238 occurrence of retrieval screening due the above-mentioned internal tests are about 4.0% and
 239 0.1% for the correlation and smoothness tests, respectively. These statistics come from
 240 analyzing the output field *Aerosol_Retrieval_Screening_Flags* and as such they do not
 241 represent the absolute rates of success of each individual test. That is because the tests are
 242 performed in a sequential order and if one of them fails, tests that are next in sequence are not
 243 performed. For standard aerosol product generation, the order is: upstream cloud mask
 244 described in 4.1.1, the brightness test, the correlation test, and the smoothness test. For



example, the correlation test is only performed on pixels that already passed the upstream cloud tests as well as the brightness test. Additionally, the brightness test does not have its own flag in the *Aerosol_Retrieval_Screening_Flags* output but is grouped together with the upstream cloud classifiers.

4.2. Retrieval screening using regional cloud parameters

Methods described in section 4.1 focus on identifying and excluding cloudy 1.1 km x 1.1 km subregions from the aerosol retrieval process. The retrieval region consists of 16 (4 x 4) subregions. These methods are highly effective at removing cloud-contaminated pixels, but since they rely on MISR visible wavelengths they might miss certain cloud signatures more easily detected in the infrared spectrum (e.g., Gao et al., 1993). For example, MODIS routinely uses its reflective and emissive infrared channels to detect optically thin cirrus clouds (Ackerman et al., 2010; Levy et al., 2013). As a result, MISR cloud detection methods occasionally fail, which leads to visible outliers in retrieved AODs (Witek et al., 2018b). For that reason, an additional set of screenings is applied in an effort to eliminate such unusually high AOD retrievals (Garay et al., 2020). Two of these additional methods look at overall cloudiness in the retrieval region (consisting of 4 x 4 subregions) as well as in a larger area consisting of 3 x 3 regions (12 x 12 subregions). The Cloud Screening Parameter (CSP) represents the fraction of clear grid cells within a region, whereas Cloud Screening Parameter Neighbor 3x3 (CSP9) is similar to CSP but for the larger area. If CSP is below 0.7 and CSP9 below 0.5, the retrieval is not reported in the final product intended for most users. However, it is still included in the product's AUXILIARY subcategory and annotated with the term "Raw" to indicate that the product has not undergone recommended quality screenings.

4.3. Adjusting cloud screening thresholds

4.3.1. Performance of the prototype NRT product

This subsection presents results and analysis of prototype NRT aerosol retrievals. These are obtained prior to any threshold and screening adjustments included in the final version of the product. To differentiate between the final and the prototype NRT products, the latter is denoted as NRT_{prot}.



As mentioned in the previous section, the NRT processing cannot rely on the cloud masks generated in the L1 and L2 cloud products, namely the RCCM, SDCM, and ASCM. This implies that potentially less screening of cloudy subregions would be applied, increasing the probability of cloud contamination in aerosol retrievals. However, some of the burden of cloud identification is picked up by the built-in cloud tests described in section 4.1.2. The frequency of these tests identifying cloudy pixels increases in NRT processing in comparison to standard processing, in large part mitigating the negative consequences resulting from the lack of the upstream cloud masks. This is well evidenced by examining the normalized probability density functions (*pdfs*) of AOD from spring 2020 (Figure 2). The FIRSTLOOK (red) and NRT_{prot} (blue) lines are very similar, indicating that the built-in cloud tests substitute to a significant extent for the missing upstream cloud masks in generating the NRT_{prot} product. The largest difference occurs in the high-AOD range, suggesting that NRT_{prot} has more retrievals in this regime. The black dotted line shows a *pdf* of the NRT_{prot} AOD retrievals that do not have a matching FIRSTLOOK retrieval. This is labeled as “NRT gained” as it represents additional retrievals obtained in NRT processing due to the lack of external cloud masks. The “NRT gained” *pdf* is clearly shifted towards higher AODs, confirming that the NRT_{prot} processing tends to retrieve higher AODs in places where FIRSTLOOK is not available.

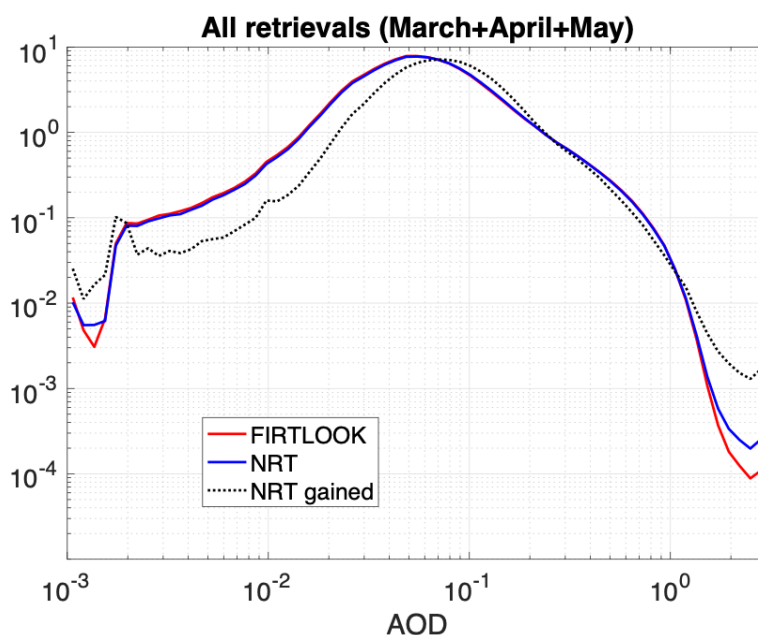


Figure 2 AOD normalized probability density functions from FIRSTLOOK, prototype NRT, and prototype NRT retrievals that do not have a matching FIRSTLOOK equivalent (labeled as NRT gained). Data statistics are provided in Table 1.



Figure 3 shows *pdfs* of AOD but with retrievals separated between DW (Fig. 3a) and land (Fig. 3b). These *pdfs* indicate that the retrievals over oceans are the main source of increased frequency of high-AODs in the NRT_{prot} product. The *pdfs* over land are virtually unchanged, including a similar distribution of the “NRT gained” retrievals (Fig. 3b). The additional statistics of the data presented in Figs. 2 and 3, including the retrieval count, the mean AOD, and the geometric mean AOD, which is better suited for log-normal distributions of AOD (Sayer et al. 2020), are provided in Table 1.

In the 3-month period analyzed in this study (March, April, May, 2020), the NRT_{prot} processing leads to about 6.5% more retrievals than FIRSTLOOK (see Table 1). 5.4 million NRT_{prot} retrievals do not have a matching FIRSTLOOK retrieval (NRT gained), and the majority of them (68%) are DW retrievals. The overall geometric means are almost identical in FIRSTLOOK and NRT_{prot}, although small variations in this statistic are seen in DW and land categories. The NRT gained have visibly higher mean and geometric mean values, the increase coming mainly from DW retrievals. These basic statistics warrant a further look at the NRT_{prot} performance over DW.

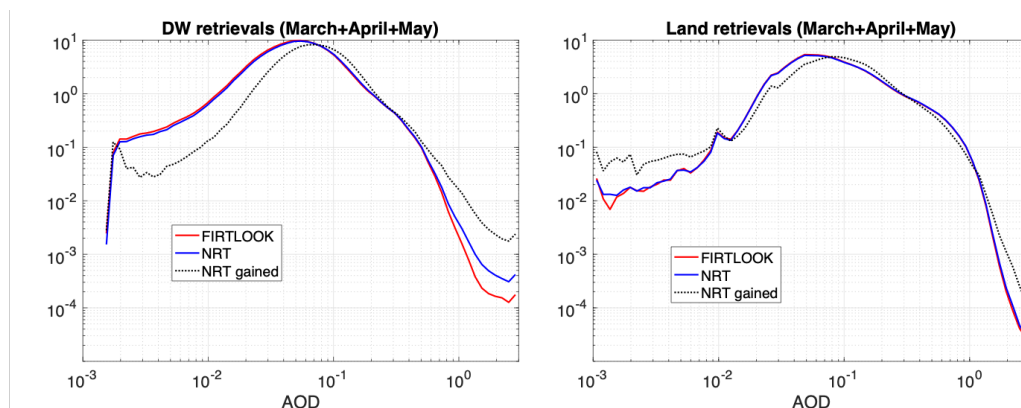


Figure 3 Same as in Fig. 2 but with retrievals separated between DW (a) and land (b). Data statistics are provided in Table 1.

	All retrievals			DW			Land		
	FL	NRT	NRT gained	FL	NRT	NRT gained	FL	NRT	NRT gained
$N (\times 10^6)$	50.4	53.7	5.4	27.9	31.1	3.7	22.5	22.6	1.7
<i>mean</i>	0.167	0.167	0.172	0.110	0.115	0.146	0.237	0.240	0.228



<i>geomean</i>	0.110	0.111	0.121	0.082	0.085	0.106	0.157	0.159	0.161
----------------	-------	-------	-------	-------	-------	-------	-------	-------	-------

Table 1 Additional statistics for the data presented in Figs. 2 and 3. FL stand for FIRSTLOOK; NRT gained stands for the prototype NRT retrievals that do not have a matching FIRSTLOOK equivalent; geomean stands for the geometric mean AOD.

4.3.2. Sensitivity to CSP and CSP9 thresholds in DW retrievals

One way to screen potentially cloud-contaminated high-AOD retrievals is to adjust thresholds on CSP and CSP9 parameters (Garay et al., 2020). This is furthermore justified by the fact that in the absence of RCCM, SDCM, and ASCM in NRT_{prot} processing, less cloudy subregions are identified in a retrieval area and consequently CSP and CSP9 have by default lower values. This argument provides strong justification for investigating sensitivity to increased CSP and CSP9 thresholds in the NRT_{prot} processing.

The standard product uses the thresholds of CSP=0.7 and CSP9=0.5 (Garay et al., 2020); when the values of CSP and CSP9 are below these thresholds in a retrieval region, the aerosol retrieval is removed from the data field recommended for users. Figure 4 and Table 2 show *pdfs* and AOD statistics for different thresholds of CSP and CSP9 parameters in the NRT_{prot} product over dark water surfaces. There are only minor changes in the *pdfs* when the thresholds are increased, including in the high-AOD regime. The mean and geometric mean decrease gradually but slowly; even at the highest considered thresholds (0.85 for CSP and 0.75 for CSP9) these statistics are still above the FIRSTLOOK values. At the same time the number of passing NRT_{prot} retrievals decreases considerably faster, with over 19% of retrievals lost when the highest thresholds are used. These results indicate that adjusting CSP and CSP9 thresholds is not an effective strategy to constraining NRT_{prot} retrievals.

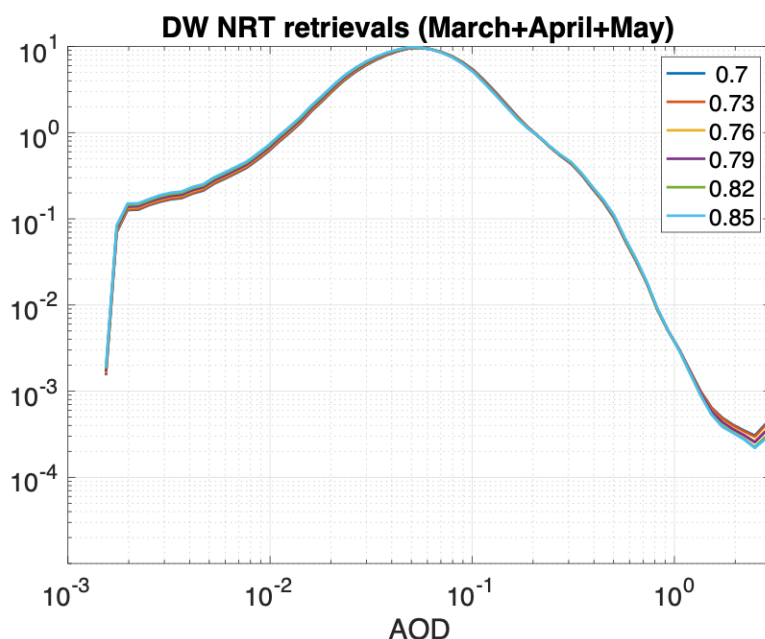


Figure 4 Prototype NRT AOD pdfs over dark water surfaces from spring 2020 obtained with different CSP and CSP9 cloud-screening thresholds. Data statistics are provided in Table 2.

$N (\times 10^6)$	31.1	30.5 (-1.7%)	28.8 (-7.3 %)	28.1 (-9.7%)	26.2 (-15.6%)	25.1 (-19.2%)	FIRSTLOOK 27.9
CSP	≥ 0.7	≥ 0.73	≥ 0.76	≥ 0.79	≥ 0.82	≥ 0.85	
CSP9	≥ 0.5	≥ 0.55	≥ 0.6	≥ 0.65	≥ 0.7	≥ 0.75	
mean	0.1147	0.1145	0.1141	0.114	0.1138	0.1139	0.1105
geomean	0.0848	0.0846	0.0840	0.0837	0.0832	0.0830	0.0824

Table 2 Additional statistics for the data presented in Fig. 4. Values for CSP and CSP9 indicate their corresponding thresholds for screening AOD retrievals.

4.3.3. Sensitivity to ARCI threshold in DW retrievals

V23 of the MISR aerosol product introduced a new parameter, called the aerosol retrieval confidence index (ARCI), that is used to screen high-AOD retrieval outliers caused by cloud contamination and other factors (Witek et al., 2018b). ARCI, defined only for DW retrievals,



proved to be an efficient metric at filtering out potentially cloud-contaminated AOD retrievals. In standard processing, retrievals with $ARCI < 0.15$ are removed from the recommended user field, but are retained in the AUXILIARY group. The 0.15 threshold is well supported through statistical analysis (Witek et al., 2018b), although some erroneous AODs still pass this screening method, suggesting that increasing this threshold might be beneficial in NRT processing.

Figure 5 and Table 3 show *pdfs* and AOD statistics for different thresholds of ARCI in the NRT_{prot} product. In this case the differences between ARCI thresholds are quite noticeable, especially in the high-AOD range of retrievals. Increasing the ARCI threshold to 0.2 leads to a loss of about 11% of NRT_{prot} DW retrievals, but the resulting mean and geometric mean are lower than the FIRSTLOOK values. At the same time, the absolute number of NRT_{prot} DW retrievals (27.8 million) is still comparable to the number of FIRSTLOOK DW retrievals (27.9 million). The *pdfs* and the statistics suggest that increasing the NRT_{prot} ARCI threshold from 0.15 to 0.18 leads to a product that has similar characteristics to FIRSTLOOK.

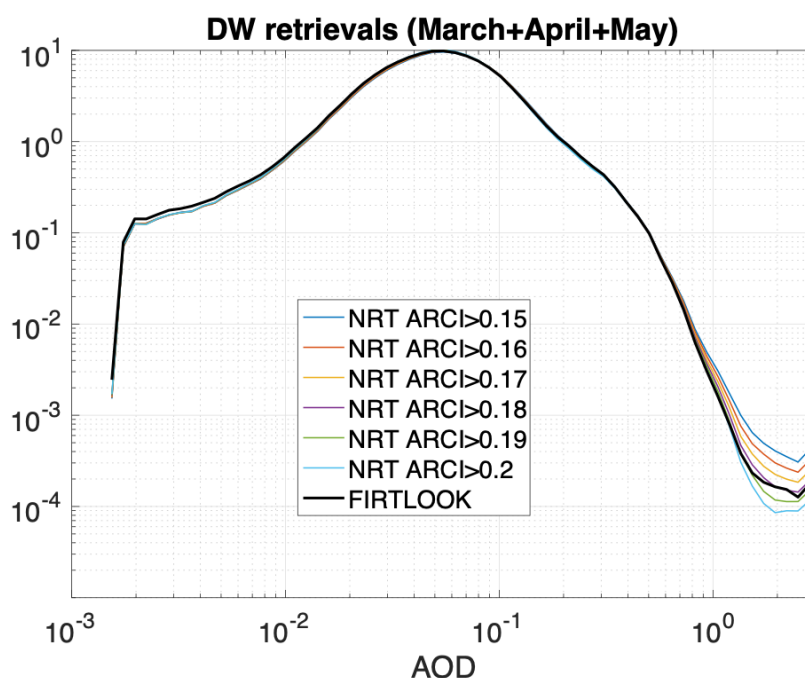


Figure 5 Prototype NRT AOD *pdfs* from spring 2020 obtained with different ARCI thresholds. Data statistic are provided in Table 3.



$N (\times 10^6)$	31.1	30.4 (-2.2%)	29.8 (-4.3%)	29.1 (-6.5%)	28.4 (-8.7%)	27.8 (-10.8%)	Firstlook 27.9
ARCI	≥ 0.15	≥ 0.16	≥ 0.17	≥ 0.18	≥ 0.19	≥ 0.20	
mean	0.1147	0.1133	0.1120	0.1108	0.1096	0.1086	0.1105
geomean	0.0849	0.0841	0.0834	0.0826	0.0819	0.0812	0.0824

Table 3 Additional statistic for the data presented in Fig. 5.

4.3.4. Recommendation for NRT processing

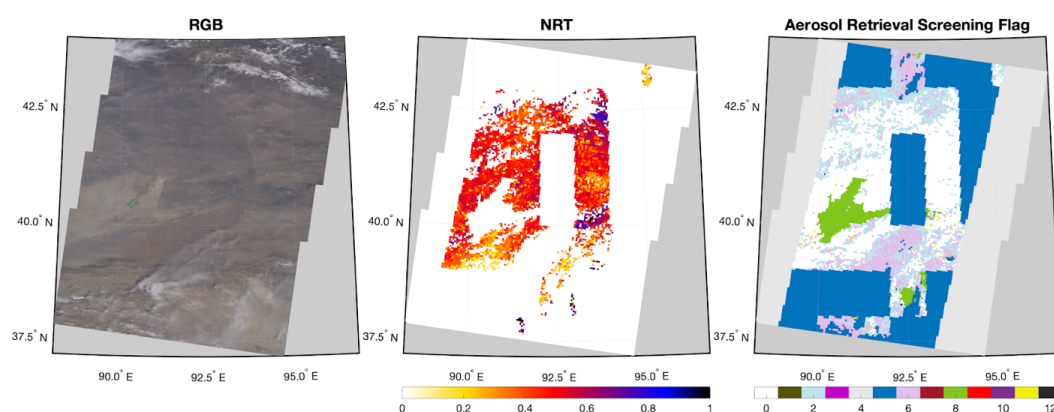
The statistical analyses presented in the previous sections indicate that the lack of RCCM, SDCM, and ASCM in NRT processing has negative consequences on the product, especially by allowing more, potentially cloud-contaminated, high-AOD DW retrievals to pass screening criteria. Adjusting build-in cloud screening thresholds on CSP and CSP9 brings only limited benefits at the cost of losing a considerable percentage of retrievals. However, the ARCI threshold adjustments result in much closer statistical correspondence between the NRT_{prot} and FIRSTLOOK AOD retrievals. For that reason, a revised ARCI threshold of 0.18 is implemented in NRT processing. Since the unscreened retrievals are also provided in the AUXILIARY group of the product, users are encouraged to experiment with their own thresholds which might prove more beneficial in specific applications or geographic areas.

4.4. Cloud/clear decision logic over snow/ice

In section 4.1.1 the impact of upstream cloud classifiers in standard processing—namely the RCCM, SDCM, and ASCM—on the subregion’s cloud/clear designation was briefly described. The decision pathway depends on the underlying surface type, which can be either land, water, or snow/ice. Over land and water, the “cloud” outcome is only obtained when both RCCM and SDCM designate the subregion as cloudy. In the absence of RCCM and SDCM the default outcome is “clear”. Over snow/ice, however, the logic is more restrictive and favors the “cloudy” designation (Diner et al., 2008). Specifically, when the upstream cloud classifiers are not available, the subregion designation is set to “cloudy” by default. This has important implications on aerosol retrievals in areas where snow and ice occur seasonally.



391 The snow/ice surface mask, unlike land and water, is not static and changes every
 392 month. Furthermore, the snow/ice mask input to MISR aerosol processing has a 1.0-degree
 393 horizontal resolution, which is re-gridded to a 1.1 km resolution corresponding to the resolution
 394 of MISR subregion. In standard processing, FIRSTLOOK retrievals use the snow/ice mask from
 395 the same month but in the previous year. The final processing is performed when the current
 396 year's monthly snow/ice mask becomes available. The NRT processing, similarly to
 397 FIRSTLOOK, relies on the previous year's snow/ice mask. Additionally, given the lack of
 398 upstream cloud classifiers, the snow/ice areas are designated as "cloudy" for aerosol retrieval
 399 purposes. This is well visualized in Figure 6 which shows the visible image and the
 400 corresponding maps of AOD and Aerosol Retrieval Screening Flag in the NRT processing. The
 401 dark blue color (index 5) denotes cloudy regions determined using the snow/ice cloud logic. The
 402 box-like nature of the excluded areas is associated with the coarse resolution of the snow/ice
 403 mask (1.0 degree). The previous year's mask might also not be representative of the current
 404 conditions on the ground. It is worth noting that the FIRSTLOOK product often suffers from the
 405 same exclusion rules as NRT. This is because of the strict clear/cloud logic over snow/ice
 406 surfaces which favors the cloudy outcome; in the case shown in Fig. 6 the AOD gaps in
 407 FIRSTLOOK (not shown) look very similar to the NRT product.



408
 409 *Figure 6 Example of snow/ice masking in NRT AOD retrievals. (Left) Visible image of the retrieval area. (Center) Corresponding*
 410 *NRT AOD retrievals. (Right) NRT Aerosol Retrieval Screening Flag for the same area; the dark blue color denotes regions*
 411 *designated as cloudy.*

412 Several attempts have been made by the MISR science team to improve NRT aerosol
 413 retrievals in snow/ice covered areas. However, identifying and isolating snow-covered surfaces
 414 in the absence of upstream cloud classifiers proves very challenging. The quality of aerosol
 415 retrievals is often negatively affected in such conditions. For that reason, and in an attempt to



416 eliminate as many NRT AOD outliers as possible, the current snow/ice logic is retained in the
417 NRT aerosol processing.

418

419 **5. NRT and FIRSTLOOK differences**

420

421 In this section, geographic distributions of MISR AOD retrievals from FIRSTLOOK and NRT
422 products are analyzed. The datasets encompass three months, March, April, and May of 2020.
423 The NRT AOD retrievals are screened with the revised ARCI threshold of 0.18 as suggested in
424 section 4.3.4. The spatial overlap of the FIRSTLOOK and NRT data is achieved using an
425 intersect of the X_Dim and Y_Dim fields in the two data products.

426 Figure 7 shows the global distributions of geometric mean AOD from the (a)
427 FIRSTLOOK and (b) NRT products. The retrievals are gridded at 2-by-2-degree spatial
428 resolution. Fig. 7c shows the AOD difference between the two products.

429 The largest AOD differences are seen in areas with climatologically high cloud cover,
430 especially over the Southern Ocean. In those regions the FIRSTLOOK AODs are predominantly
431 higher than the NRT AODs. This is due to the increased ARCI threshold in NRT (0.18 vs. 0.15
432 in FIRSTLOOK) which brings in more aggressive screening of cloud-contaminated retrievals
433 (Witek et al., 2018b). At the same time the lack of cloud classifiers in NRT does not adversely
434 affect AOD distributions, which is consistent with the statistical analysis presented in section
435 4.2.3.

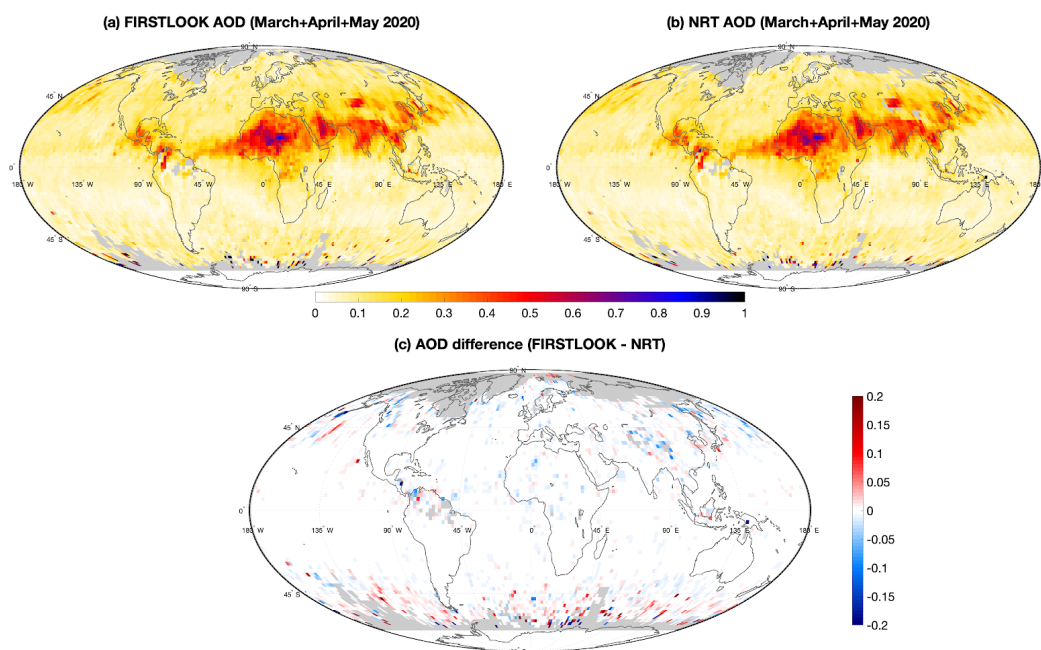


Figure 7 (a) Global distribution of FIRSTLOOK AOD geometric mean values across March, April, and May of 2020 on a 2-by-2-degree spatial resolution; (b) same as in (a) but for NRT AOD; and (c) AOD difference between FIRSTLOOK and NRT.

Figure 8 complements Fig. 7 by showing (a) the FIRSTLOOK retrieval count distribution as well as (b) the retrieval count difference between the FIRSTLOOK and NRT products.

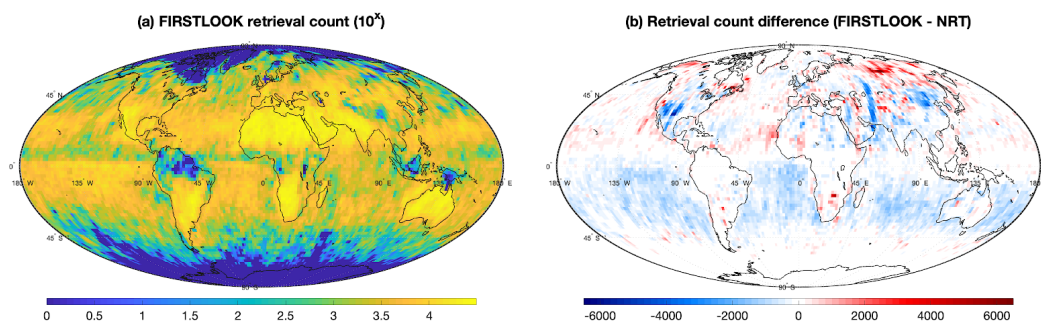


Figure 8 (a) Decimal logarithm of the retrieval count from the FIRSTLOOK product in March, April, and May of 2020; (b) retrieval count difference between FIRSTLOOK and NRT. Presented values are gridded at 2-by-2-degree spatial resolution

The highest number of retrievals is found over the subtropical continents where the cloud cover is usually the smallest. Over the subtropical oceans in the Southern Hemisphere the NRT retrieval counts are typically lower than in FIRSTLOOK, which is attributed to the increased



447 ARCI threshold in DW retrievals. The lack of hemispheric symmetry in this case is likely due to
 448 the seasonal variability (only months in northern spring are analyzed here). The conservative
 449 cloud logic over snow/ice surfaces in NRT results in the lower number of retrievals in the high
 450 latitudes of the northern hemisphere.

451

452 **6. Summary**

453

454 The MISR V23 aerosol product, publicly available since mid-2018, is a high-resolution state-of-
 455 the-art data product from NASA's Terra flagship mission. V23 AOD retrievals have remarkable
 456 accuracy compared against ground-based observations (Garay et al., 2020; Tao et al., 2020;
 457 Witek et al., 2019) and the product is more intuitive and easier to use than previous versions.
 458 The product is available within 2 days from satellite overpass as a FIRSTLOOK version, and
 459 within 3-to-6 months as a final science-quality “standard” version that employs the most up-to-
 460 date ancillary datasets. In response to the needs of operational user communities, a new MISR
 461 L2 NRT aerosol product has been developed with a 3-hour latency.

462 The new NRT algorithm does not depend on the upstream cloud classifiers that are
 463 generated in L1 and L2 cloud processing. The lack of cloud classifiers is in large part mitigated
 464 by the aerosol algorithm’s built-in cloud identification methods. Analysis has shown an
 465 increased frequency of high-AOD retrievals, especially over oceans and in climatologically
 466 cloudy areas, likely due to an increase in cloud contamination. Adjusting the ARCI threshold in
 467 DW retrievals proves highly effective at eliminating some of these high-AOD outliers and
 468 improves the NRT product’s statistical agreement with the FIRSTLOOK version. The new NRT
 469 aerosol product applies an ARCI threshold of 0.18 to mitigate cloud contamination in the
 470 absence of upstream cloud masks in NRT processing. The remaining differences in statistical
 471 and geographic distributions between NRT and FIRSTLOOK, which includes information from
 472 the L2 cloud product, are small and largely confined to areas with high cloud cover.

473 The results of this study also serve as an example of the effects of screening threshold
 474 adjustments in MISR aerosol retrievals on AOD statistics and distributions. Researchers
 475 interested in particular applications and/or specific geographic regions are encouraged to
 476 experiment with their own threshold to achieve most optimal results.

477

478 **Acknowledgements**



479 This research was carried out at the Jet Propulsion Laboratory, California Institute of
480 Technology, under a contract with the National Aeronautics and Space Administration. Support
481 from the MISR project is acknowledged. All data analyzed in this study are publicly available,
482 although the transient nature of FIRSTLOOK and NRT products might limit their availability. The
483 data can be downloaded from <https://l0dup05.larc.nasa.gov/cgi-bin/MISR/main.cgi>.

484

485



486 **References:**

- 487 Ackerman, S., Richard, F., Kathleen, S., Yinghui, L., Liam, G., Bryan, B. and Paul, M.:
 488 Discriminating clear-sky from cloud with MODIS algorithm theoretical basis document
 489 (MOD35), Univ. Wisconsin - Madison, 6th Edn.(October), 129 [online] Available from:
 490 <http://citeserx.ist.psu.edu/viewdoc/summary?doi=10.1.1.385.4885>, 2010.
- 491 Bocquet, M., Elbern, H., Eskes, H., Hirtl, M., Aabkar, R., Carmichael, G. R., Flemming, J.,
 492 Inness, A., Pagowski, M., Pérez Camaño, J. L., Saide, P. E., San Jose, R., Sofiev, M., Vira, J.,
 493 Baklanov, A., Carnevale, C., Grell, G. and Seigneur, C.: Data assimilation in atmospheric
 494 chemistry models: Current status and future prospects for coupled chemistry meteorology
 495 models, *Atmos. Chem. Phys.*, 15(10), 5325–5358, doi:10.5194/acp-15-5325-2015, 2015.
- 496 Buchard, V., Da Silva, A. M., Colarco, P. R., Darmenov, A., Randles, C. A., Govindaraju, R.,
 497 Torres, O., Campbell, J. and Spurr, R.: Using the OMI aerosol index and absorption aerosol
 498 optical depth to evaluate the NASA MERRA Aerosol Reanalysis, *Atmos. Chem. Phys.*, 15(10),
 499 5743–5760, doi:10.5194/acp-15-5743-2015, 2015.
- 500 Butz, A., Hasekamp, O. P., Frankenberg, C. and Aben, U.: Retrievals of atmospheric CO₂ from
 501 simulated space-borne measurements of backscattered near-infrared sunlight: Accounting for
 502 aerosol effects, *Appl. Opt.*, 48, 3322–3336, doi:10.1364/AO.48.003322, 2009.
- 503 Choi, M., Lim, H., Kim, J., Lee, S., Eck, T. F., Holben, B. N., Garay, M. J., Hyer, E. J., Saide, P.
 504 E. and Liu, H.: Validation, comparison, and integration of GOCI, AHI, MODIS, MISR, and
 505 VIIRS aerosol optical depth over East Asia during the 2016 KORUS-AQ campaign, *Atmos.*
 506 *Meas. Tech.*, 12(8), 4619–4641, doi:10.5194/amt-12-4619-2019, 2019.
- 507 Colarco, P., Da Silva, A., Chin, M. and Diehl, T.: Online simulations of global aerosol
 508 distributions in the NASA GEOS-4 model and comparisons to satellite and ground-based aerosol
 509 optical depth, *J. Geophys. Res. Atmos.*, 115(14), doi:10.1029/2009JD012820, 2010.
- 510 Diner, D. J., Beckert, J. C., Reilly, T. H., Bruegge, C. J., Conel, J. E., Kahn, R. A., Martonchik,
 511 J. V., Ackerman, T. P., Davies, R., Gerstel, S. A. W., Gordon, H. R., Muller, J. P., Myneni, R. B.,
 512 Sellers, P. J., Pinty, B. and Verstraete, M. M.: Multiangle Image Spectroradiometer (MISR)



- 513 instrument description and experiment overview, IEEE Trans. Geosci. Remote Sens., 36(4),
 514 1072–1087, 1998.
- 515 Diner, D. J., Di Girolamo, L. and Clothiaux, E. E.: Level 1 Cloud Detection Algorithm
 516 Theoretical Basis, Jet Propuls. Lab. Calif. Inst. Technol., D-13397(Rev. B), 1999a.
- 517 Diner, D. J., Davies, R., Di Girolamo, L., Horvath, A., Moroney, C., Muller, J. P., Paradise, S.
 518 R., Wenkert, D. and Zong, J.: Level 2 Cloud Detection and Classification Algorithm Theoretical
 519 Basis, Jet Propuls. Lab. Calif. Inst. Technol., D-11399(Rev. D), 1999b.
- 520 Diner, D. J., Abdou, W. A., Ackerman, T. P., Crean, K., Gordon, H. R., Kahn, R. A.,
 521 Martonchik, J. V., McMuldroy, S., Paradise, S. R. and Pinty, B.: Level 2 aerosol retrieval
 522 algorithm theoretical basis, Jet Propuls. Lab. Calif. Inst. Technol., D-11400(Rev. G), 2008.
- 523 Frankenberg, C., Hasekamp, O., O'Dell, C., Sanghavi, S., Butz, A. and Worden, J.: Aerosol
 524 information content analysis of multi-angle high spectral resolution measurements and its benefit
 525 for high accuracy greenhouse gas retrievals, Atmos. Meas. Tech., 5(7), 1809–1821,
 526 doi:10.5194/amt-5-1809-2012, 2012.
- 527 Frouin, R. J., Franz, B. A., Ibrahim, A., Knobelspiesse, K., Ahmad, Z., Cairns, B., Chowdhary,
 528 J., Dierssen, H. M., Tan, J., Dubovik, O., Huang, X., Davis, A. B., Kalashnikova, O., Thompson,
 529 D. R., Remer, L. A., Boss, E., Coddington, O., Deschamps, P. Y., Gao, B. C., Gross, L.,
 530 Hasekamp, O., Omar, A., Pelletier, B., Ramon, D., Steinmetz, F. and Zhai, P. W.: Atmospheric
 531 Correction of Satellite Ocean-Color Imagery During the PACE Era, Front. Earth Sci., 7,
 532 doi:10.3389/feart.2019.00145, 2019.
- 533 Fu, G., Prata, F., Xiang Lin, H., Heemink, A., Segers, A. and Lu, S.: Data assimilation for
 534 volcanic ash plumes using a satellite observational operator: A case study on the 2010
 535 Eyjafjallajökull volcanic eruption, Atmos. Chem. Phys., 17(2), 1187–1205, doi:10.5194/acp-17-
 536 1187-2017, 2017.
- 537 Gao, B. C., Goetz, A. F. H. and Wiscombe, W. J.: Cirrus cloud detection from Airborne Imaging
 538 Spectrometer data using the 1.38 μm water vapor band, Geophys. Res. Lett., 20(3), 301–304,
 539 doi:10.1029/93GL00106, 1993.



- 540 Garay, M. J., Witek, M. L., Kahn, R. A., Seidel, F. C., Limbacher, J. A., Bull, M. A., Diner, D.
 541 J., Hansen, E. G. E. G., Kalashnikova, O. V., Lee, H., Nastan, A. M. and Yu, Y.: Introducing the
 542 4.4km spatial resolution Multi-Angle Imaging SpectroRadiometer (MISR) aerosol product,
 543 Atmos. Meas. Tech., 13(2), 593–628, doi:10.5194/amt-13-593-2020, 2020.
- 544 Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., Randles, C. A.,
 545 Darmenov, A., Bosilovich, M. G., Reichle, R., Wargan, K., Coy, L., Cullather, R., Draper, C.,
 546 Akella, S., Buchard, V., Conaty, A., da Silva, A. M., Gu, W., Kim, G. K., Koster, R., Lucchesi,
 547 R., Merkova, D., Nielsen, J. E., Partyka, G., Pawson, S., Putman, W., Rienecker, M., Schubert,
 548 S. D., Sienkiewicz, M. and Zhao, B.: The modern-era retrospective analysis for research and
 549 applications, version 2 (MERRA-2), J. Clim., 30(14), 5419–5454, doi:10.1175/JCLI-D-16-
 550 0758.1, 2017.
- 551 Girolamo, L. Di and Davies, R.: A Band-Differenced Angular Signature Technique for Cirrus
 552 Cloud Detection, IEEE Trans. Geosci. Remote Sens., 32(4), 890–896, doi:10.1109/36.298017,
 553 1994.
- 554 Girolamo, L. Di and Davies, R.: The Image Navigation Cloud Mask for the Multiangle Imaging
 555 Spectroradiometer (MISR), J. Atmos. Ocean. Technol., 12(6), doi:10.1175/1520-
 556 0426(1995)012<1215:tincmf>2.0.co;2, 1995.
- 557 Gordon, R.: Atmospheric correction of ocean color imagery in the Earth Observing System era,
 558 J. Geophys. Res. - Atmos., 102(D14), 17081–17106, doi:10.1029/96JD02443, 1997.
- 559 Houweling, S., Hartmann, W., Aben, I., Schrijver, H., Skidmore, J., Roelofs, G. J. and Breon, F.
 560 M.: Evidence of systematic errors in SCIAMACHY-observed CO₂ due to aerosols, Atmos.
 561 Chem. Phys., 5(11), 3003–3013, doi:10.5194/acp-5-3003-2005, 2005.
- 562 Inness, A., Baier, F., Benedetti, A., Bouarar, I., Chabrillat, S., Clark, H., Clerbaux, C., Coheur,
 563 P., Engelen, R. J., Errera, Q., Flemming, J., George, M., Granier, C., Hadji-Lazaro, J., Huijnen,
 564 V., Hurtmans, D., Jones, L., Kaiser, J. W., Kapsomenakis, J., Lefever, K., Leitão, J., Razinger,
 565 M., Richter, A., Schultz, M. G., Simmons, A. J., Suttie, M., Stein, O., Thépaut, J. N., Thouret,
 566 V., Vrekoussis, M. and Zerefos, C.: The MACC reanalysis: An 8 yr data set of atmospheric
 567 composition, Atmos. Chem. Phys., 13(8), 4073–4109, doi:10.5194/acp-13-4073-2013, 2013.



- 568 Inness, A., Ades, M., Agustí-Panareda, A., Barré, J., Benedictow, A., Blechschmidt, A.-M.,
 569 Dominguez, J. J., Engelen, R., Eskes, H., Flemming, J., Huijnen, V., Jones, L., Kipling, Z.,
 570 Massart, S., Parrington, M., Peuch, V.-H., Razinger, M., Remy, S., Schulz, M. and Suttie, M.:
 571 The CAMS reanalysis of atmospheric composition, *Atmos. Chem. Phys.*, 19(6), 3515–3556,
 572 doi:10.5194/acp-19-3515-2019, 2019.
- 573 IPCC: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to
 574 the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, edited by T. F.
 575 Stocker, D. Qin, G. K. Plattner, M. M. B. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia,
 576 V. Bex, and P. M. Midgley, Cambridge University Press, Cambridge, United Kingdom and New
 577 York, NY, USA., 2013.
- 578 Kahn, R. A. and Gaitley, B. J.: An analysis of global aerosol type as retrieved by MISR, J.
 579 *Geophys. Res. Atmos.*, 120(9), 4248–4281, doi:10.1002/2015JD023322, 2015.
- 580 Kahn, R. A., Gaitley, B. J., Garay, M. J., Diner, D. J., Eck, T. F., Smirnov, A. and Holben, B. N.:
 581 Multiangle Imaging SpectroRadiometer global aerosol product assessment by comparison with
 582 the Aerosol Robotic Network, *J. Geophys. Res. Atmos.*, 115(23), doi:10.1029/2010JD014601,
 583 2010.
- 584 Kalashnikova, O. V., Garay, M. J., Martonchik, J. V. and Diner, D. J.: MISR Dark Water aerosol
 585 retrievals: Operational algorithm sensitivity to particle non-sphericity, *Atmos. Meas. Tech.*, 6(8),
 586 2131–2154, doi:10.5194/amt-6-2131-2013, 2013.
- 587 Lamarque, J. F., Shindell, D. T., Josse, B., Young, P. J., Cionni, I., Eyring, V., Bergmann, D.,
 588 Cameron-Smith, P., Collins, W. J., Doherty, R., Dalsoren, S., Faluvegi, G., Folberth, G., Ghan,
 589 S. J., Horowitz, L. W., Lee, Y. H., MacKenzie, I. A., Nagashima, T., Naik, V., Plummer, D.,
 590 Righi, M., Rumbold, S. T., Schulz, M., Skeie, R. B., Stevenson, D. S., Strode, S., Sudo, K.,
 591 Szopa, S., Voulgarakis, A. and Zeng, G.: The atmospheric chemistry and climate model
 592 intercomparison Project (ACCMIP): Overview and description of models, simulations and
 593 climate diagnostics, *Geosci. Model Dev.*, 6(1), 179–206, doi:10.5194/gmd-6-179-2013, 2013.
- 594 Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D. and Pozzer, A.: The contribution of outdoor
 595 air pollution sources to premature mortality on a global scale, *Nature*, 525(7569), 367–371,



- 596 doi:10.1038/nature15371, 2015.
- 597 Levy, R. C., Mattoo, S., Munchak, L. A., Remer, L. A., Sayer, A. M., Patadia, F. and Hsu, N. C.:
 598 The Collection 6 MODIS aerosol products over land and ocean, *Atmos. Meas. Tech.*, 6(11),
 599 2989–3034, doi:10.5194/amt-6-2989-2013, 2013.
- 600 Liu, M., Westphal, D. L., Walker, A. L., Holt, T. R., Richardson, K. A. and Miller, S. D.:
 601 COAMPS real-time dust storm forecasting during operation Iraqi freedom, *Weather Forecast.*,
 602 22(1), 192–206, doi:10.1175/WAF971.1, 2007.
- 603 Lynch, P., Reid, J. S., Westphal, D. L., Zhang, J., Hogan, T. F., Hyer, E. J., Curtis, C. A., Hegg,
 604 D. A., Shi, Y., Campbell, J. R., Rubin, J. I., Sessions, W. R., Turk, F. J. and Walker, A. L.: An
 605 11-year global gridded aerosol optical thickness reanalysis (v1.0) for atmospheric and climate
 606 sciences, *Geosci. Model Dev.*, 9(4), 1489–1522, doi:10.5194/gmd-9-1489-2016, 2016.
- 607 Martonchik, J. V., Kahn, R. A. and Diner, D. J.: Retrieval of aerosol properties over land using
 608 MISR observations, in *Satellite Aerosol Remote Sensing over Land*, pp. 267–293, Springer
 609 Berlin Heidelberg, 2009.
- 610 Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., Bosilovich, M.
 611 G., Schubert, S. D., Takacs, L., Kim, G. K., Bloom, S., Chen, J., Collins, D., Conaty, A., Da
 612 Silva, A., Gu, W., Joiner, J., Koster, R. D., Lucchesi, R., Molod, A., Owens, T., Pawson, S.,
 613 Pegion, P., Redder, C. R., Reichle, R., Robertson, F. R., Ruddick, A. G., Sienkiewicz, M. and
 614 Woollen, J.: MERRA: NASA’s modern-era retrospective analysis for research and applications,
 615 *J. Clim.*, 24, 3624–3648, doi:10.1175/JCLI-D-11-00015.1, 2011.
- 616 Sayer, A. M., Govaerts, Y., Kolmonen, P., Lipponen, A., Luffarelli, M., Mielonen, T., Patadia,
 617 F., Popp, T., Povey, A. C., Stebel, K. and Witek, M. L.: A review and framework for the
 618 evaluation of pixel-level uncertainty estimates in satellite aerosol remote sensing, *Atmos. Meas.*
 619 *Tech.*, 13(2), 373–404, doi:10.5194/amt-13-373-2020, 2020.
- 620 Sekiyama, T. T., Tanaka, T. Y., Shimizu, A. and Miyoshi, T.: Data assimilation of CALIPSO
 621 aerosol observations, *Atmos. Chem. Phys.*, 10(1), 39–49, doi:10.5194/acp-10-39-2010, 2010.
- 622 Shi, Y., Zhang, J., Reid, J. S., Holben, B., Hyer, E. J. and Curtis, C.: An analysis of the collection



- 623 5 MODIS over-ocean aerosol optical depth product for its implication in aerosol assimilation,
 624 Atmos. Chem. Phys., 11(2), 557–565, doi:10.5194/acp-11-557-2011, 2011.
- 625 Shi, Y., Zhang, J., Reid, J. S., Hyer, E. J. and Hsu, N. C.: Critical evaluation of the MODIS Deep
 626 Blue aerosol optical depth product for data assimilation over North Africa, Atmos. Meas. Tech.,
 627 6(4), 949–969, doi:10.5194/amt-6-949-2013, 2013.
- 628 Shi, Y., Zhang, J., Reid, J. S., Liu, B. and Hyer, E. J.: Critical evaluation of cloud contamination
 629 in the MISR aerosol products using MODIS cloud mask products, Atmos. Meas. Tech., 7(6),
 630 1791–1801, doi:10.5194/amt-7-1791-2014, 2014.
- 631 Shindell, D. T., Lamarque, J. F., Schulz, M., Flanner, M., Jiao, C., Chin, M., Young, P. J., Lee,
 632 Y. H., Rotstayn, L., Mahowald, N., Milly, G., Faluvegi, G., Balkanski, Y., Collins, W. J.,
 633 Conley, A. J., Dalsoren, S., Easter, R., Ghan, S., Horowitz, L., Liu, X., Myhre, G., Nagashima,
 634 T., Naik, V., Rumbold, S. T., Skeie, R., Sudo, K., Szopa, S., Takemura, T., Voulgarakis, A.,
 635 Yoon, J. H. and Lo, F.: Radiative forcing in the ACCMIP historical and future climate
 636 simulations, Atmos. Chem. Phys., 13(6), 2939–2974, doi:10.5194/acp-13-2939-2013, 2013.
- 637 Si, Y., Chen, L., Xiong, X., Shi, S., Husi, L. and Cai, K.: Evaluation of the MISR fine resolution
 638 aerosol product using MODIS, MISR, and ground observations over China, Atmos. Environ.,
 639 223(December 2019), 117229, doi:10.1016/j.atmosenv.2019.117229, 2020.
- 640 Sogacheva, L., Popp, T., Sayer, A. M., Dubovik, O., Garay, M. J., Heckel, A., Hsu, N. C.,
 641 Jethva, H., Kahn, R. A., Kolmonen, P., Kosmale, M., de Leeuw, G., Levy, R. C., Litvinov, P.,
 642 Lyapustin, A., North, P., Torres, O. and Arola, A.: Merging regional and global aerosol optical
 643 depth records from major available satellite products, Atmos. Chem. Phys., 20(4), 2031–2056,
 644 doi:10.5194/acp-20-2031-2020, 2020.
- 645 Tao, M., Wang, J., Li, R., Chen, L., Xu, X., Wang, L., Tao, J., Wang, Z. and Xiang, J.:
 646 Characterization of Aerosol Type Over East Asia by 4.4 km MISR Product: First Insight and
 647 General Performance, J. Geophys. Res. Atmos., 125(13), 1–16, doi:10.1029/2019JD031909,
 648 2020.
- 649 Di Tomaso, E., Schutgens, N. A. J., Jorba, O. and García-Pando, C. P.: Assimilation of MODIS



- 650 Dark Target and Deep Blue observations in the dust aerosol component of NMMB-MONARCH
 651 version 1.0, *Geosci. Model Dev.*, 10(3), 1107–1129, doi:10.5194/gmd-10-1107-2017, 2017.
- 652 Turnock, S. T., Allen, R. J., Andrews, M., Bauer, S. E., Deushi, M., Emmons, L., Good, P.,
 653 Horowitz, L., John, J. G., Michou, M., Nabat, P., Naik, V., Neubauer, D., O'Connor, F. M.,
 654 Olivie, D., Oshima, N., Schulz, M., Sellar, A., Shim, S., Takemura, T., Tilmes, S., Tsigaridis, K.,
 655 Wu, T. and Zhang, J.: Historical and future changes in air pollutants from CMIP6 models,
 656 *Atmos. Chem. Phys.*, 20(23), 14547–14579, doi:10.5194/acp-20-14547-2020, 2020.
- 657 Werner, M., Kryza, M. and Guzikowski, J.: Can data assimilation of surface PM_{2.5} and Satellite
 658 AOD improve WRF-Chem Forecasting? A case study for two scenarios of particulate air
 659 pollution episodes in Poland, *Remote Sens.*, 11(20), doi:10.3390/rs11202364, 2019.
- 660 Witek, M. L., Garay, M. J., Diner, D. J. and Smirnov, A.: Aerosol optical depths over oceans: A
 661 view from MISR retrievals and collocated MAN and AERONET in situ observations, *J.*
 662 *Geophys. Res. Atmos.*, 118(22), 12620–12633, doi:10.1002/2013JD020393, 2013.
- 663 Witek, M. L., Diner, D. J., Garay, M. J., Xu, F., Bull, M. A. and Seidel, F. C.: Improving MISR
 664 AOD Retrievals with Low-Light-Level Corrections for Veiling Light, *IEEE Trans. Geosci.*
 665 *Remote Sens.*, 56(3), 1251–1268, doi:10.1109/TGRS.2017.2727342, 2018a.
- 666 Witek, M. L., Garay, M. J., Diner, D. J., Bull, M. A. and Seidel, F. C.: New approach to the
 667 retrieval of AOD and its uncertainty from MISR observations over dark water, *Atmos. Meas.*
 668 *Tech.*, 11(1), 429–439, doi:10.5194/amt-11-429-2018, 2018b.
- 669 Witek, M. L., Garay, M. J., Diner, D. J. and Smirnov, A.: Oceanic Aerosol Loading Derived
 670 From MISR's 4.4 km (V23) Aerosol Product, *J. Geophys. Res. Atmos.*, 124(17–18), 10154–
 671 10174, doi:10.1029/2019JD031065, 2019.
- 672 Xian, P., Reid, J. S., Hyer, E. J., Sampson, C. R., Rubin, J. I., Ades, M., Asencio, N., Basart, S.,
 673 Benedetti, A., Bhattacharjee, P. S., Brooks, M. E., Colarco, P. R., da Silva, A. M., Eck, T. F.,
 674 Guth, J., Jorba, O., Kouznetsov, R., Kipling, Z., Sofiev, M., Perez Garcia-Pando, C., Pradhan,
 675 Y., Tanaka, T., Wang, J., Westphal, D. L., Yumimoto, K. and Zhang, J.: Current state of the
 676 global operational aerosol multi-model ensemble: An update from the International Cooperative



677 for Aerosol Prediction (ICAP), Q. J. R. Meteorol. Soc., 145, 176–209, doi:10.1002/qj.3497,
678 2019.

679 Zhang, J. and Reid, J. S.: An analysis of clear sky and contextual biases using an operational
680 over ocean MODIS aerosol product, Geophys. Res. Lett., 36(15), doi:10.1029/2009GL038723,
681 2009.

682 Zhang, J. and Reid, J. S.: A decadal regional and global trend analysis of the aerosol optical
683 depth using a data-assimilation grade over-water MODIS and Level 2 MISR aerosol products,
684 Atmos. Chem. Phys., 10(22), 10949–10963, doi:10.5194/acp-10-10949-2010, 2010.

685 Zhang, J., Reid, J. S., Westphal, D. L., Baker, N. L. and Hyer, E. J.: A system for operational
686 aerosol optical depth data assimilation over global oceans, J. Geophys. Res. Atmos., 113(10), 1–
687 13, doi:10.1029/2007JD009065, 2008.

688