

1 **Integration of GOCI and AHI Yonsei Aerosol Optical Depth** 2 **Products During the 2016 KORUS-AQ and 2018 EMeRGe** 3 **Campaigns**

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16 **Abstract.** The Yonsei AErosol Retrieval (YAER) algorithm for the Geostationary Ocean
17 Color Imager (GOCI) retrieves aerosol optical properties only over dark surfaces, so it is
18 important to mask pixels with bright surfaces. The Advanced Himawari Imager (AHI) is
19 equipped with three shortwave-infrared and nine infrared channels, which is advantageous for
20 bright-pixel masking. In addition, multiple visible and near-infrared channels provide a great
21 advantage in aerosol property retrieval from the AHI and GOCI. By applying the YAER
22 algorithm to 10 minute AHI or 1 hour GOCI data at 6 km × 6 km resolution, diurnal
23 variations and aerosol transport can be observed, which has not previously been possible
24 from low-earth-orbit satellites. This study attempted to estimate the optimal aerosol optical
25 depth (AOD) for East Asia by data fusion, taking into account satellite retrieval uncertainty.
26 The data fusion involved two steps: (1) analysis of error characteristics of each retrieved
27 result with respect to the ground-based Aerosol Robotic Network (AERONET), and bias
28 correction based on normalized difference vegetation indexes; and (2) compilation of the
29 fused product using ensemble-mean and maximum-likelihood estimation methods (MLE).
30 Fused results show a better statistics in terms of fraction within the expected error, correlation
31 coefficient, root-mean-square error, median bias error than the retrieved result for each
32 product. If the root mean square error and Gaussian center values used for MLE fusion are
33 correct, the MLE fused products show better accuracy, but the ensemble-mean products can
34 still be used as useful as MLE.

35 **1. Introduction**

36 Aerosols are generated by human activities and natural processes on local to global scales,
37 and have a lifetime of several to tens of days. Aerosols affect Earth's radiative energy balance
38 by scattering and absorption (e.g. Cho et al., 2003). High aerosol loadings are persistent in
39 Northeast Asia, including diverse aerosol types from various sources. Interactions among
40 aerosols, clouds, and radiation in the atmosphere cause significant uncertainties in climate-
41 model calculations (IPCC, 2013). Datasets produced by satellites have been widely used to
42 reduce such uncertainties (Saide et al., 2014; Pang et al., 2018), but the systems must be

43 accurately calibrated, verified, and consistent. Satellite data have been used extensively to
44 retrieve aerosol optical properties (AOPs) over broad areas, with several algorithms having
45 been developed. Satellites in low earth orbit (LEO), including Sun-synchronous orbit (SSO),
46 cover the entire Earth over one to several days, depending on instrument and orbit
47 characteristics. Most aerosol retrieval algorithms have been developed for LEO satellites
48 (Kim et al., 2007; Lyapustin et al., 2011a, b; Lee et al., 2012; Fukuda et al., 2013; Hsu et al.,
49 2013; Levy et al., 2013; Garay et al., 2017, 2020). LEO instruments currently onboard
50 satellites include the Moderate Resolution Imaging Spectrometer (MODIS), Visible Infrared
51 Imaging Radiometer Suite (VIIRS), Multi-angle Imaging SpectroRadiometer (MISR), and
52 Cloud and Aerosol Imager (CAI) (Remer et al., 2005; Lyapustin et al., 2011a, b, 2018;
53 Fukuda et al., 2013; Hsu et al., 2013; Levy et al., 2013; Garay et al., 2017, 2020; Jackson et
54 al., 2013; Lee et al., 2017).

55 Representative algorithms developed for MODIS data include the Dark-Target (DT; Remer
56 et al., 2005; Levy et al., 2013), Deep Blue (DB; Hsu et al., 2013; Sayer et al., 2014), and
57 Multi-Angle Implementation of Atmospheric Correction (MAIAC; Lyapustin et al., 2011a, b)
58 systems, which are also applied for the succeeding VIIRS (Sayer et al., 2018). In the DT
59 algorithm, the 2.1 μm channel is used to estimate land-surface reflectance in the visible (VIS)
60 region using empirical equations based on the normalized difference vegetation index
61 (NDVI). The DT algorithm has improved surface-reflectance modelling through
62 consideration of the fractional area of urbanization (Gupta et al., 2016). Ocean-surface
63 reflectance is estimated using the Cox and Munk method (Cox and Munk, 1954), and AOPs
64 over land and ocean are provided at spatial resolutions of 10 km \times 10 km and 3 km \times 3 km
65 (Remer et al., 2013), respectively. The DB algorithm has an advantage over the DT algorithm
66 in allowing aerosol data retrieval over bright surfaces. By using a shorter-wavelength channel,
67 accuracy is improved over bright surfaces such as urban and desert areas, where surface
68 reflectance was previously estimated by the minimum reflectance method (MRM; Herman
69 and Celarier 1997; Koelemeijer et al., 2003; Hsu et al., 2004). Furthermore, with the
70 improvement to Collection 6.1, land-surface reflectance can be estimated similarly to the DT
71 method, over densely vegetated regions (Sayer et al., 2019). In the case of VIIRS DB, aerosol
72 retrieval over the ocean is also applied by the Satellite Ocean Aerosol Retrieval (SOAR)
73 algorithm (Sayer et al., 2018). In the MODIS MAIAC system, surface reflectance is
74 estimated by considering various images based on time-series analysis, with multi-angle
75 observations, based on up to 16 day data, and by applying the bidirectional reflectance
76 distribution function (BRDF). Ocean-surface reflectance is determined using a Cox and
77 Munk BRDF model similar to DT and VIIRS DB (Lyapustin et al., 2011a, b, 2018). The
78 MISR observes Earth at nine different angles, providing a high degree of freedom for signals;
79 consequently, retrievals yield estimates of aerosol type and shape. As with the MAIAC,
80 multiple observations are used, with the estimation of land-surface reflectance involving
81 bidirectional reflectance factors (BRF). Zhang et al. (2016) developed an aerosol retrieval
82 algorithm that allows aerosol data retrieval over bright land surfaces using surface-reflectance
83 ratios from the VIIRS.

84 Aerosol retrieval algorithms for geosynchronous Earth orbit (GEO) satellites have been
85 developed, including the Geostationary Operational Environmental Satellite (GOES) series in
86 the USA (Knapp et al., 2005), Meteosat series in Europe (Bernard et al., 2011), Himawari
87 series in Japan (Yoon et al., 2007; Kim et al., 2008; Lim et al., 2018; Kikuchi et al., 2018;
88 Yoshida et al., 2018; Gupta et al., 2019), and the Geostationary Korea Multi-Purpose Satellite
89 (GEO-KOMPSAT, GK) series in South Korea (Kim et al., 2014, 2016; Choi et al., 2016,
90 2018; Kim et al., 2020). However, previously launched geostationary meteorological
91 satellites had only a single, broadband VIS channel, with which it is difficult to retrieve

AOPs other than aerosol optical depth (AOD) (Wang et al., 2003; Knapp et al., 2005; Kim et al., 2008, 2014, 2016; Bernard et al., 2011). However, the Geostationary Ocean Color Imager (GOCI) onboard the GK-1 satellite, also known as the Communication, Ocean, and Meteorological Satellite (COMS), has six VIS and two near-infrared (NIR) channels, which is advantageous for retrieving AOPs (Lee et al., 2010; Choi et al., 2016, 2018; Kim et al., 2017). Next-generation meteorological GEO satellite instruments, including the Advanced Himawari Imager (AHI), Advanced Baseline Imager (ABI), and Advanced Meteorological Imager (AMI), have three to four VIS and NIR channels, which enable aerosol property retrieval with high accuracy (Lim et al., 2016, 2018; Kikuchi et al., 2018; Yoshida et al., 2018; Gupta et al., 2019). Kikuchi et al. (2018) and Yoshida et al. (2018) performed aerosol retrievals using the MRM and corrected reflectance using empirical equations. Gupta et al. (2019) extended the MODIS DT algorithm to GEO satellites and estimated visible surface reflectance using SWIR reflectance. Lim et al. (2018) retrieved the AOPs using both MRM and estimated surface reflectance from short-wave IR (SWIR) data (ESR), and presented the two merged products: an L2-AOD merged product, and a reprocessed AOD produced by merging MRM and ESR surface reflectances. The MRM gives better accuracy over brighter surfaces such as urban areas, while the ESR method gives better accuracy over areas of dense vegetation (Lim et al., 2018). However, there is a critical surface reflectance at which aerosol signals disappear, depending on the single-scattering albedo (Kim et al., 2016). Over the ocean, both the MRM and ESR methods give high accuracy, but ESR results are robust with the Cox and Munk model.

The MRM requires more computational time than the ESR method to estimate surface reflectance, as it requires data for the past 30 days, and LER needs to be calculated using a radiative transfer model. The ESR method estimates surface reflectance from the observed TOA reflectance at 1.6 μm wavelength using empirical equations including the NDVI. The advantage of MRM is that stable surface reflectance values can be obtained regardless of surface type. However, due to the influence of background aerosol optical depth (BAOD), surface reflectance tends to be overestimated, with satellite-derived AOD data thus being underestimated (Kim et al., 2014). On the other hand, the ESR method uses TOA reflectance at 1.6 μm wavelength to detect surface signals, which is less sensitive to fine particles and BAOD. However, when aerosols such as yellow dust with coarse particles are transported from the Taklamakan and Gobi deserts, the BAOD effect also applies to the ESR method. The ESR method is also more likely to be affected by snow surfaces than the MRM, as snow reduces reflectivity around the 1.6 μm wavelength (Negi and Kokhanovsky, 2011). The ESR method also has the disadvantage of giving noisy results over bright surfaces such as desert. However, its fast surface-reflectance estimation enables near-real-time retrieval based on the AHI YAER algorithm.

Algorithms developed to date for LEO and GEO satellites have both advantages and disadvantages, depending on algorithm characteristics. Therefore, the MODIS team provides combined DT and DB AOD products (Levy et al., 2013; Sayer et al., 2014). In addition, several studies of the fusion of L2 products have been conducted (Levy et al., 2013; Sayer et al., 2014; Wei et al., 2019), with Bilal et al. (2017) obtaining reliable results from merged DT and DB products, as indicated by the NDVI in East Asia, and also robust products by simply averaging DT and DB without consideration of the NDVI.

AOP data fusion in East Asia may also be achieved using aerosol products of AMI, GOCI-2, and the geostationary environment monitoring spectrometer (GEMS) onboard the GK-2A and 2B satellites launched by South Korea in 2018 and 2020, respectively, with accuracy over bright surfaces being improved by the GEMS aerosol product. It is also possible to obtain

141 accurate AOPs, such as single-scattering albedo, aerosol loading height, and fine-mode
142 fraction, which have been difficult to obtain by fusion of L2 data and/or surface reflectance
143 data. If the trace-gas dataset retrieved from GEMS is used, it is possible to improve the
144 aerosol type, with the retrieval of high-quality AOD data (Go et al., 2020).

145 Several studies have considered AOD data fusion, for which methods can be broadly
146 classified into two types. First, the fusion of more than one AOD product may involve
147 optimal interpolation (Xue et al., 2012), linear or second-order polynomial functions (Mélin
148 et al., 2007), arithmetic or weighted means (Gupta et al., 2008), or maximum-likelihood
149 estimates (MLE) (Nirala, 2008; Xu et al., 2015; Xie et al., 2018). Second, in the absence of
150 satellite-derived AOD products for the day of fusion, the geostatistical fusion method,
151 universal kriging method (Chatterjee et al., 2010; Li et al., 2014), geostatistical inverse
152 modelling (Wang et al., 2013), or spatial statistical data fusion (Nguyen et al., 2012) may be
153 applied. These have the advantage that AOD can be estimated by integrating the spatial
154 autocorrelation of AOD data even for pixels missing from the AOD products, although there
155 is a disadvantage in not considering temporal correlations. The Bayesian maximum entropy
156 (BME) method, taking into account temporal autocorrelation, has also been developed (Tang
157 et al., 2016). BME methodology can estimate gap-filling pixels that are difficult to retrieve
158 due to clouds, but with somewhat reduced accuracy. Gap filled AOD using the BME method,
159 and satellite-derived AOD discontinuity arises from insufficient temporal sampling being
160 available with the use of LEO satellites, resulting in a low fusion synergy. Previous studies
161 mentioned above include data fusion based on Kriging, reproduction of spectral AOD, and
162 BME method. Most of them focus on gap filling and rebuild AOD in areas not observed by
163 MISR, MODIS, and SeaWiFS, and so on (Wang et al., 2013; Tang et al., 2016). However in
164 this study, we focused on optimized AOD products with improved accuracy at the retrieved
165 pixels by ensemble-mean and MLE fusion. We compared these two products, one very
166 simple one and the other with more elaborated processes. As previous AOD fusion studies
167 improved the retrieved results mainly based on MLE or NDVI-based fusion studies (Bilal et
168 al., 2017; Levy et al., 2013; Wei et al., 2019; Go et al., 2020), we tried to further improve
169 them with efficient approach to save computation time considering the nature of satellite data
170 file size and user's near-real-time demand for data assimilation.

171 In this study, the GEO satellite dataset was used to resolve the temporal sampling issue for
172 data fusion, while maintaining the spatio-temporal resolution retrieved from GEO satellites.
173 We also attempted to estimate fused AOD products at 550nm with higher accuracy in East
174 Asia. The ensemble-mean and MLE methods were applied. Section 2 describes the two
175 algorithms used in this study for AHI and GOCI. Section 3 mentions methods of fusion and
176 systematic bias correction, and section 4 performs validation of the fused products with the
177 Aerosol Robotic Network (AERONET) instruments during two field campaigns: the Korea–
178 United States Air Quality Study (KORUS-AQ) and the Effect of Megacities on the Transport
179 and Transformation of Pollutants on Regional and Global Scales Study (EMeRGe).

180 2. Descriptions of AHI, GOCI, the YAER algorithm

181 2.1 AHI aerosol algorithm

182 The Himawari-8 and -9 satellites were launched by the Japanese Meteorological Agency
183 (JMA) on 7 October 2014 and 2 November 2016, respectively. The AHI onboard these
184 satellites has 16 channels covering wavelengths of 0.47–13.3 μm and performs full-disk and
185 Japan-area observations every 10 and 2.5 min, respectively, from GEO at 140.7° E longitude
186 (Bessho et al., 2016). Visible and NIR observations are also performed at high spatial

187 resolutions of 0.5–1.0 km, with SWIR to IR at 2 km, which have advantages in aerosol
188 property retrieval and cloud masking.

189 Lim et al. (2018) developed the AHI Yonsei aerosol retrieval (YAER) algorithm and
190 provided two retrieval results with 6 km × 6 km resolution based on MRM and ESR using
191 SWIR data. Aerosol property retrieval using VIS channels requires accurate surface
192 reflectance, for which MRM and ESR are useful, with the main difference between the two
193 lying in the surface-reflectance estimation method.

194 The MRM applies the minimum-reflectance technique over both land and ocean (Lim et al.,
195 2018), with surface reflectance being estimated by finding the minimum reflectance in each
196 pixel over the past 30 day window, giving the Lambertian equivalent reflectance (LER; Kim
197 et al., 2016; Lim et al., 2018). This method takes the bidirectional characteristics of surface
198 reflectance into consideration by obtaining surface reflectance at each observation time over
199 the 30-day search window. However, the method assumes that there is more than one clear
200 day during the search window and that surface reflectance does not change; otherwise, it is
201 affected by clouds and/or the BAOD (Kim et al., 2014; Kim et al., 2021).

202 According to the ESR method, land-surface reflectance in the VIS region is constructed
203 from the Top of Atmosphere (TOA) reflectance at 1.6 μ m wavelength, based on the NDVI
204 for SWIR and the fraction of urbanization and cropland (Levy et al 2013; Gupta et al., 2016;
205 Zhong et al., 2016; Lim et al., 2018). Ocean-surface reflectance is estimated from the Cox
206 and Munk BRDF model (Cox and Munk, 1954). Chlorophyll-a concentrations are considered
207 in addition to Chlorophyll-a concentration data
208 (<https://www.eorc.jaxa.jp/ptree/userguide.html>) from Japan Aerospace Exploration Agency
209 (JAXA) (Murakami et al., 2016) and interpolated for the 10-min AHI intervals. For
210 unretrieved pixels, the less contaminated chlorophyll-a concentration value of 0.02 mg m⁻³ is
211 used. Details of the methodology can be found in Lim et al. (2018).

212 **2.2 GOCI aerosol algorithm**

213 GOCI is an ocean color imager in GEO launched onboard COMS in 2010 and observes the
214 East Asia region at an hourly interval with 500 m × 500 m resolution (Choi et al., 2012). It has
215 eight bands in the VIS and NIR regions, which is advantageous for aerosol retrieval. Two
216 versions of GOCI Yonsei aerosol algorithms have been developed, referred to as V1 and V2
217 (Lee et al., 2010; Choi et al., 2016, 2018). In the case of V1, surface reflectance is estimated
218 by the MRM using LER for the past 30 days over land, and the Cox and Munk BRDF model
219 over oceans. In V2, ocean-surface reflectance is estimated by the same method, but land-
220 surface reflectance is improved by using an accumulated long-term database. To minimize
221 the impact of BAOD (the weakness of the MRM), a monthly surface-reflectance database
222 was constructed using all of the LERs over the past five years, but it cannot reflect
223 unexpected changes in surface conditions. However, a well-established climatological
224 database allows aerosol property retrieval in near-real-time with reasonable accuracy.

225

226 **3. Data fusion methods**

227 Satellite-derived AODs have different error characteristics depending on NDVI, scattering
228 angle, and so on (Choi et al., 2016, 2018; Lim et al., 2018). Over oceans, ESR AODs are
229 more accurate than MRM AODs. However, the accuracy of GOCI AODs was dependent on
230 the NDVI values, which represent surface condition in terms of vegetation. V1 has a negative
231 bias and V2 has a mostly a positive bias (Choi et al., 2018). In this study, we developed

232 optimal AOD products at 550 nm in East Asia by fusing four individual retrievals, i.e. two
233 AHI aerosol products from the MRM and ESR methods, and two GOCI products from V1
234 and V2.

235 **3.1 Spatio-temporal matching**

236 The AHI and GOCI have different spatial pixel locations and temporal resolutions, so it is
237 necessary to match their spatio-temporal resolutions before data fusion. GOCI and AHI
238 AODs have the same spatial resolution of $6 \text{ km} \times 6 \text{ km}$, but the two satellites are located at
239 128.2° E and 140.7° E , respectively, at the equator. Spatial pixel matching is therefore
240 required. However, satellite-derived AOD represents total-column extinction, so AOD
241 retrieved by the two sensors is not significantly affected by satellite position. To merge the
242 different satellite spatial pixel coverages, the GOCI pixel was re-gridded to match AHI pixels
243 for full-disk observation, with up to 4 GOCI AOD pixels being used with average values
244 considered representative of pixel values. If more than half of the AHI AOD pixels did not
245 exist out of the maximum 6 AHI data per hour, it is regarded as cloud contaminated pixels
246 and an additional cloud removal process is performed. This process applies to both the MRM
247 and ESR method, to remove the AHI's additional cloud-contaminated pixels in products of
248 both GOCI V1 and V2, which have a disadvantage in cloud masking due to their lack of IR
249 channels. When three or more pixels were available for generating AHI data at 1 hour
250 intervals, hourly AOD values were estimated as the medians of pixel values.

251 **3.2 Ensemble-mean method**

252 Here, AMR represents AHI MRM AOD, AES represents AHI ESR AOD, GV1 represents
253 GOCI V1 AOD, and GV2 represents GOCI V2 AOD. We performed data fusion using AMR,
254 AES, GV1, and GV2 data within 1 hour intervals for which additional-cloud masking was
255 performed. The ensemble-mean is the mean of the ensemble member over a specific time.
256 The ensemble members are AMR, AES, GV1, and GV2 based on two satellite instruments
257 and two different surface-estimation methodologies. Table 1 provides the satellite-derived
258 AOD used for ensemble-mean and MLE fusion.

259 Fusion was performed only when a pixel of an ensemble member was used for all fusions.
260 Fusion 1 (F1) included the two AHI products of AMR and AES, and two GOCI products of
261 GV1 and GV2. Fusion 2 (F2) involved the calculation of the YAER algorithm by the fusion
262 of AES and GV2, both of which have the advantage of producing data in near-real-time.
263 Fusion 3 (F3) merged AMR and AES to estimate AOD over a wide area, and Fusion 4 (F4)
264 involved a comparison with F1 to determine how accuracy varied with decreasing number of
265 ensemble members, as summarized in Table 1.

266 **3.3 MLE method**

267 Similarly, FM1, FM2, and FM3 is the result of MLE fusion corresponding to F1, F2, and F3
268 as in ensemble mean, respectively (see Table 1).

269 The MLE method provides a means of weighting and averaging based on errors evaluated
270 with AERONET ground-based measurements (Nirala, 2008; Xu et al., 2015; Xie et al., 2018).

271 This method employs the following equations:

$$\tau_i^{MLE} = \sum_{k=1}^N \frac{R_{i,k}^{-2}}{\sum_{k=1}^N R_{i,k}^{-2}} \tau_{i,k} \quad (1)$$

$$R_{i,k} = \sqrt{\frac{\sum_{i=1}^M (s_{i,k} - g_i)^2}{M}} \quad (2)$$

272 where τ_i^{MLE} represents the fused AOD; $\tau_{i,k}$ represents the mean AOD at grid point i from the
 273 satellite-derived AOD product k , where k is the index for different satellite-derived AOD
 274 products for fusion; $R_{i,k}$ represents the root-mean-square error (RMSE) at grid point i for the
 275 satellite-derived AOD product k ; N is the number of all AOD data; g_i represents the mean of
 276 ground-based AOD at grid point i from the AERONET (collocated temporal mean); $s_{i,k}$
 277 represents the mean of satellite derived AOD products (k) at grid points of the AERONET
 278 (collocated spatial mean); and M is the number of pairs of $s_{i,k}$ and g_i .

279 For RMSE estimation, bias correction, validation, and error estimation (details in Sec.5),
 280 AERONET Version 3 Level 2.0 aerosol products were used for ground truth (Giles et al.,
 281 2019; Smirnov et al., 2000; Holben et al., 2001). RMSE and bias correction value for each
 282 satellite product (details in Sec.3.4) required for MLE fusion were calculated through
 283 comparison with AERONET from Apr. 2018 to Mar. 2019 excluding EMeRGe period. The
 284 number of AERONET sites used for validation and error estimation in this study, was 35
 285 during the KORUS-AQ campaign, and 22 during the EMeRGe campaign, for AHI and GOCI
 286 products.

287 Satellite observation can cover wide areas, but the ground observation instrument cannot
 288 cover all satellite observed areas. Therefore, a RMSE model was constructed for AOD, time,
 289 and NDVI through comparative validation with AERONET observation as shown in Figure 1.
 290 For MLE over wide areas without ground measurements, the calculated RMSE from AOD,
 291 time, and NDVI bins was applied for every satellite pixel. We excluded points that AOD
 292 differences with respect to AERONET data (dAOD) were > 2 standard deviations (SD) to
 293 remove outliers and to consider only the more stable RMSE values. According to Figure 1, if
 294 the AOD is less than 0.5, RMSE is about 0.1 with respect to all NDVI bins, but if the AOD is
 295 greater than 0.5, the overall RMSE value becomes large. All products excluding AES show
 296 large variations for high NDVI and high AOD bin as shown as the red square in Figure 1,
 297 especially for 02 UTC and 05 UTC of two GOCI products and 00 UTC in AMR product.
 298 This is because the two GOCI products and AMR are relatively less accurate for densely
 299 vegetated areas, along with sampling issues.

300 3.4 Bias correction

301 AOD follows a log-normal distribution (Sayer and Knobelspiesse, 2019), but dAOD for
 302 each satellite product follow a Gaussian distribution. The quantile–quantile (Q-Q) plot is a
 303 graphical statistical technique that compares two probability distributions with each other.
 304 The x-axis represents the quantile value of the directly calculated sample, and the y-axis
 305 represents the Z-score. Here, the Z-score is a dimensionless value that makes a statistically
 306 Gaussian distribution and shows where each sample is located on the standard deviation. That
 307 is, when Z-score of 1 and 2 represent 1 SD and 2 SD, respectively. In addition, as the Q-Q
 308 plot shows a linear shape, the sample follows a Gaussian distribution.

309 Figure 2 shows dAOD divided by SD analyzed for each satellite product, for the period
 310 from April 2018 to March 2019, excluding the EMeRGe campaign, which shows a similar
 311 pattern to the standard Gaussian distribution. However, if the theoretical quantile values are
 312 greater than 0.5, then the sample quantile values are smaller than the standard Gaussian
 313 values. Also, when the theoretical quantile is less than 0.5, the opposite results are shown.

314 Thus, the sample quantiles are more skewed at both sides than the theoretical quantile, but the
315 respective satellite product follows the Gaussian distribution.

316 The bias center for each satellite product was calculated differently for time and NDVI bins
317 through Gaussian fitting in Figure 3 of the dAOD divided by SD (except for 2SD and higher),
318 and subtracted from respective product for correction. Data beyond 2 SD of dAOD were
319 excluded to prevent a change in bias trends due to AOD errors caused by cloud shadows and
320 cloud contamination. This process was performed before applying the MLE method, which
321 allows compensation for systematic bias that is difficult to obtain directly in MLE.

323 **3.5 Evaluation of aerosol products during two field campaigns**

324 The performance of the respective satellite product and fused products was analyzed in two
325 field campaigns: the KORUS-AQ of 1 May 2016 to 12 Jun 2016 (<https://www-air.larc.nasa.gov/missions/korus-aq/>), and the EMeRGe of 12 Mar 2018 to 8 Apr 2018
326 (<https://www.halo.dlr.de/science/missions/emerge/emerge.html>). KORUS-AQ was an
327 international multi-organization mission to observe air quality across the Korean Peninsula
328 and surrounding waters, led by the US National Aeronautics and Space Administration
329 (NASA) and the Korean National Institute of Environmental Research (NIER) (Crawford et
330 al., 2021). EMeRGe aimed to investigate experimentally the patterns of atmospheric transport
331 and transformation of pollution plumes originating from Eurasia, tropical and subtropical
332 Asian megacities, and other major population centers. GEO satellite data played an important
333 role in these campaigns; e.g., data assimilation for chemical transport models and tracking
334 aerosol plumes (Saide et al., 2014, 2010; Pang et al., 2018).

335 In this study, we used satellite-derived GOCI and AHI AODs, with a spatial resolution of 6
336 km × 6 km, and temporal resolutions of 1 hour and 10 minutes, respectively. Spatio-temporal
337 correlation between satellite-derived AOD and AERONET AOD involved data averaged over
338 all satellite pixels within a 25 km radius of the AERONET site, and AERONET AOD
339 averaged over ±30 minutes from the satellite observation time. As validation metrics,
340 Pearson's correlation coefficient, median bias error (MBE), the fraction (%) within the
341 expected error of MODIS DT (EE), and Global Climate Observing System requirement for
342 AOD (GCOS; GCOS, 2011) were applied. The accuracy requirement of GCOS for satellite-
343 derived AOD at 550nm is 10% or 0.03, whichever is larger. The EE provided by the MODIS
344 DT algorithm (EE as $\pm 0.05 \pm 0.15 \times \text{AOD}$; (Levy et al., 2010)) was used for consistent
345 comparison with previous studies.

346 Table 2 shows the validation metrics of the respective product during the two field
347 campaigns. The collocation points for validation with AERONET of two AHI and two GOCI
348 products were not significantly different. %EE and %GCOS of AES and AMR showed better
349 accuracy than GV1 and GV2 during the KORUS and the EMeRGe periods. In terms of MBE,
350 GV2 is 0.008 and -0.001, which shows during the KORUS-AQ and the EMeRGe periods
351 close to zero. Additionally, further analyzes of the respective satellite product are carried out
352 along with fused products in Section 5.

353 **4. Results**

354 Figure 4 (a) shows the average AOD of FM1 (MLE method with all products) during the
355 KORUS-AQ period, and Figure 4 (b-e) shows the respective difference of the average AOD
356 of AMR, AES, GV1, and GV2 with respect to FM1. FM1 was selected as the representative

fused product as FM1 used all four satellite-derived products for fusion with bias correction. The result of the comparison with the respective satellite product (Figure 4 (b-e)) shows different features. AMR shows a negative bias over the ocean but shows similar results to FM1 over land, while AES shows a different tendency in northern and southern China. GV1 tends to show opposite pattern to AES, and GV2 shows positive bias over the ocean and results in similar pattern to FM1 over the land. In the west of the Korean peninsula, AES AOD has a positive offset compared to FM1. Although the AES algorithm considers the fraction of urbanization, there is still a tendency to have a positive AOD offsets. The main reason why AES results show different patterns is the different estimation process of the land surface reflectance from that of other products.

On the other hand, in GV1, the AOD over the Manchurian region has a positive offset compared to FM1. This is because the aerosol signal is small over bright surface, making it difficult to retrieve aerosol properties. These features tend to be alleviated in GV2, where the surface reflectance and cloud removal process were improved.

Figure 5 shows the same result as Figure 4 except for the EMeRGe period. The AMR and AES AODs appeared high in northern China, which is thought to be the snow contaminated pixel. The EMeRGe period was in March-April, when northern China is more covered by snow compared to the KORUS-AQ period in May-June. On the other hand, for GV1 and GV2, the effect of overestimation with snow contaminated pixel is relatively small, as their snow masking is well performed. However, for the KORUS-AQ period, it seems that the GV1's overestimation of AOD in northern China still remains. Since this analysis (Figure 4 and 5) is for the fusion between the three MRM results and one ESR result, the average field difference is naturally the largest in AES which uses ESR method.

For the characteristics of the average AOD for the two campaign period, high AODs during the KORUS-AQ period were found in eastern China, and Hokkaido as wildfires from Russia were transported to Hokkaido (Lee et al., 2019). Meanwhile, during the EMeRGe period, high AOD is shown over the Yellow sea as aerosols were transported from China to the Korean peninsula through the west coast, contrary to the KORUS-AQ period. Overall, the average AODs for the EMeRGe are less smooth than those of the KORUS-AQ period. This is because the EMeRGe period was shorter than that of the KORUS-AQ, and the retrieval accuracy was lower due to the bright surface.

5. Validation, comparison, and error estimation against AERONET

5.1 Validation for fused AOD products with AERONET

The spatio-temporal matching method between fused AOD and AERONET was performed as mentioned above in Section 3.5, and the statistics indices used for verification are also the same. Validation indices of fused products with AERONET AOD during the two campaign periods are summarized in Table 3. During the KORUS-AQ, fused AODs have better accuracy of than respective satellite product in terms of %EE and %GCOS. The %EE and %GCOS of AES, which showed the best accuracy among the respective product, are 63.5% and 43.6%, which are poor than the worst accuracy of the fused AOD. All RMSE has been improved except for FM2. The RMSE of FM2 is higher than RMSE of respective satellite product by 0.001. Although all MBEs show different patterns, the deviation of the fused products tends to be smaller. GV2 and F2 show MBE of 0.008, close to zero.

404 Next, %EE for the EMeRGe period exceeded 60.0, with AMR having the best accuracy of
405 69.4. Likewise, %GCOS was also the highest with 52.4, which showed better accuracy than
406 the fused product. In terms of MBE, GV2 was the best, with -0.001. The fused products did
407 not have the best statistical values, but they show overall better statistical values.

408 Figure 6 shows the %GCOS for the respective satellite product and fused products at each
409 validation site during each campaign. In Figure 6(a), for the KORUS period, F1 and FM1
410 show the highest % GCOS at 20 sites out of 35. Other than the fused result, AES shows the
411 highest %GCOS at 13 sites, which are mostly dense vegetation-area and coastal sites. On the
412 other hand, during EMeRGe period, the %GCOS of fused products was highest at 7 sites out
413 of 22, while respective satellite product showed at the rest of the sites in similar proportions.

415 **5.2 Error estimation**

416 Differences between satellite products and AERONET, dAOD values were analyzed in
417 terms of NDVI and observation times (Figure 7). Figure 7 (a) and (d) shows the respective
418 satellite product, Figure 7 (b) and (e) the ensemble-mean product, and Figure 7 (c) and (f) the
419 MLE fusion results, with each filled circle representing the mean of 500 and 400 collocated
420 data points sorted in terms of NDVI for the KORUS-AQ and the EMeRGe campaigns,
421 respectively. Figure 7 (a) shows different biases for each satellite product, with AMR and
422 GV1 being negative, AES and GV2 being positive. The errors are close to zero for both the
423 ensemble-mean and MLE products except for FM2 as a result of the fusion process.
424 When the NDVI is small, the Gaussian center for GV2 dAOD was close to zero, but when the
425 NDVI is large, the Gaussian center was negative as shown in Figure 3. The bias correction
426 effect of GV2 shows a small effect for small NDVI bins and a large effect for large NDVI
427 bins. In fact, the collocated dAODs of FM2 show close to zero when the NDVI bins are
428 greater than 0.4 (in Figure 7 (a)).

429 During the EMeRGe campaign (right column, Figure 7), the two AHI and two GOCI
430 products show negative biases, and even the ensemble-mean results have negative biases. The
431 ensemble-mean does not include any bias correction, meaning that the error characteristics of
432 each original satellite product are intact. The MLE products display improved biases in terms
433 of NDVI, which are close to zero because the bias was corrected for in the MLE process.
434 During the EMeRGe period, the collocated dAOD values at NDVI around 0.1 have a
435 negative value for all satellite-derived products (especially AHI products), and GV1 has a
436 negative value for bins where NDVI is greater than 0.2. During the EMeRGe period, the
437 collocated dAOD values at NDVI around 0.1 show negative values for all respective product
438 (especially AHI products), and dAOD for GV1 shows negative values for NDVI bins greater
439 than 0.2. The fused products tend to have error close to zero except for F3 and FM3. In terms
440 of F3, the collocated dAOD value around 0.1 of the NDVI bin has negative values for both
441 AMR and AES, so the collocated dAOD of F3 remain negative. Gaussian center values for
442 FM3, AMR and AES (in Figure 3) are close to zero for NDVI at around 0.1, so the bias
443 correction effect is small. This can be explained by the fact that the collocated dAOD for
444 NDVI at around 0.2 during the EMeRGe period is closer to zero in FM3 than in F3.

445 The median bias of the AOD products over the observation time was analyzed as shown in
446 Figure 8 where the left column represents the KORUS-AQ and the right column the EMeRGe
447 campaign, with filled circles representing median values, and the error bar being ± 1 SD. As
448 in the KORUS-AQ campaign, the AMR shows a generally negative bias, as in the all-time
449 results, and a negative bias also exists in each time zone. In the AES, GV1, and GV2 case,
450 positive and negative biases appear differently according to time zones. The ± 1 SD of the

451 respective satellite product is larger at local noon and smaller at 00 and 07 UTC when SZA is
452 large. Fused products as shown in Figures 8 (b) and (c), have a smaller ± 1 SD, and the
453 collocated dAOD over the observation time is also close to zero. Meanwhile, FM2 shows the
454 same tendency of overestimation for the same reason as in the previous Figure 7(a).

455 For the EMeRGe period, the collocated dAOD values of the respective product appear
456 closer to zero than KORUS-AQ. Similarly, the collocated dAOD of the fused products also
457 show values close to zero.

458 The error analysis indicates that the results after fusion are more accurate than the results
459 obtained using individual satellite product, and fused products accuracy was slightly better
460 during KORUS-AQ than EMeRGe because more data points were considered. Also, the
461 surface was relatively dark during the KORUS-AQ period, thus reduced errors for aerosol
462 retrieval than during the EMeRGe period.

463 5.3 Time-series analysis of daily mean and hourly AODs

464 The Gangneung-Wonju National University site (Gangneung-WNU; 128.87°E, 37.77°N)
465 lies on the eastern side of the Korean Peninsula and it is one of the regions with low aerosol
466 loadings. The AOD frequency distribution generally follows a log-normal distribution, and it
467 is important to evaluate accuracy for low AOD values. Therefore, we evaluated whether the
468 fused products were improved at low AODs. A daily mean time-series and diurnal variation
469 comparison of different satellite AOD products against AERONET (on a logarithmic scale)
470 are shown in Figure 9 for the Gangneung-WNU site without high AOD events, where most
471 point AERONET AODs at 550 nm were < 1 during the KORUS-AQ campaign. Daily mean
472 time-series data from the AERONET, ensemble-mean, and MLE products are shown in
473 Figure 9 (a-c), where black filled circles and black error bar represent AERONET AOD and
474 ± 1 SD of one-day average AERONET AOD. Satellite-derived AODs represented in different
475 colors show similar variabilities.

476 Respective satellite product generally shows similar daily-mean AOD distribution to
477 AERONET AOD. AMR, GV1, GV2 using MRM technique show similar patterns, and AES
478 using SWIR for surface reflectance estimation shows different patterns. The daily-mean AOD
479 of AES is more close to AERONET. On the other hand, Figure 9 (b) and (c) representing
480 fused AOD show similar patterns overall, but the daily-mean AODs on 11 May show
481 different patterns. Here, ensemble-mean products (F1-4) are less accurate than an individual
482 AES product, while MLE products (FM1-3) exhibit similar diurnal variation to daily-mean
483 AERONET AOD. To further analyze this, the daily-mean AOD is shown in Figure 9 (d-f)
484 instead of the hourly AOD for 11-14 May.

485 As in the previous daily-mean AOD results, Figure 9 (d) shows the hourly AES AOD
486 variations are close to hourly AERONET, while AMR, GV1, and GV2 tend to underestimate.
487 Similarly, as shown in Figure 9 (e), hourly AOD variation of the ensemble-mean products
488 shows overall underestimation for 11 May. All ensemble-mean products use AES as an
489 ensemble member, but do not sufficiently compensate for the negative biases held by AMR,
490 GV1, and GV2. Meanwhile, MLE fused products show similar patterns to the hourly AOD
491 variation of AERONET, such as AES outputs. This can be explained in two ways: the effect
492 of considering the weighted function based on pixel-level uncertainty (RMSE in this study)
493 and the bias correction effects. Figure 1 showed similar RMSE values for all observation
494 times when $AOD \leq 0.5$. Gangneung-WNU site is one of the densely vegetated areas, but if
495 the AOD is less or equal to 0.5, there is little sensitivity of RMSE according to NDVI bins.
496 That is, regardless of the NDVI, each satellite-specific weighting function used for the MLE
497 fusion has a similar value for all satellite-derived products. The difference between the

498 ensemble-mean and the MLE fused products is due to the bias correction considered in the
499 MLE fusion. For example, the FM3 states that AMR has a large negative bias in the
500 afternoon and AES has a negative bias in the morning. With the bias correction of AES and
501 AMR respectively in the morning and afternoon, FM3 is calibrated in a direction to
502 compensate the underestimated AOD. The effect of bias correction and MLE fusion
503 agreement varies depending on the NDVI and AOD loading for each pixel. If bias correction
504 was not performed in the case on 11 May, the MLE fusion output shows very similar values
505 to F3.

506 The MLE products were implemented in a way to improve accuracy for the low AOD
507 region more critically than in the high AOD region by systematic bias correction. In general
508 surface reflectance estimated by the MRM is affected by BAOD, to result in a negative bias
509 in AOD. On the other hand, the AES uses TOA reflectance at 1.6 μm wavelength to estimate
510 surface reflectance and is therefore less affected by BAOD, and shows higher AOD than
511 AMR and the two GOCI AODs. Furthermore, AOD retrieval over vegetated areas is more
512 accurate with the ESR method. This result is consistent with previous studies of aerosol
513 retrieval in the VIS region (Levy et al., 2013; Gupta et al., 2019; Hsu et al., 2019).
514

515 **5.4 Accuracy evaluation for AHI products of the outside of GOCI domain**

516 In this section, the AMR, AES, F3, and FM3 products were evaluated at 34 sites within the
517 0-50°N and 70-150°E except for the GOCI domain as shown in Figures 4 and 5 (112-148°E,
518 24-50°N). The evaluation results are summarized in Table 4 in terms of N, R, RMSE, MBE,
519 and GCOS fraction. The RMSE and Gaussian center values within the GOCI domain were
520 used in the MLE fusion in this section (see Figures 1 and 3). Table 4 shows the %GCOS and
521 RMSE values with poor accuracy than the validation results for the GOCI coverage as listed
522 in Table 4. In addition, BME during the KORUS-AQ and the EMeRGe period was -0.098
523 and -0.135 for AMR, and 0.130 and -0.055 for AES, respectively, which show very poor
524 accuracy. This can be explained by the cloud contamination issue at sites near the equator,
525 including Thailand. In addition, since AMR cannot collect enough clear pixels for the
526 estimation of LER, which can cause errors. Furthermore, MRM does not work well over
527 desert areas. On the other hand, AES has issues with poor accuracy over bright pixels such as
528 desert and snow contaminated areas. Second, there are many areas where the coastline is
529 complex as in Hong Kong, and the surface elevation is uneven as in Himalayas. However,
530 there is a bias of -0.055 during the EMeRGe period for AES, but the %GCOS was the highest
531 with 34.1, which is considered significant. F3 and FM3 show similar patterns for the
532 KORUS-AQ and the EMeRGe period. The accuracy of F3 is better than that of FM3, because
533 the previously mentioned issue for the bias correction has worked incorrectly, as the RMSE
534 and bias correction values used were from the data in the untrained area.
535

536 **6. Summary and conclusion**

537 Various aerosol algorithms have been developed for two different GEO satellites, AHI and
538 GOCI. Retrieved AOD data have advantages and disadvantages, depending on the concept of
539 the algorithm and surface-reflectance estimations. In this study, four aerosol products (GV1,
540 GV2, AMR, and AES) were used to construct ensemble-mean and MLE products. For the
541 ensemble-mean, this study presented fusion products taking advantage of overlap region,
542 accuracy, and near-real-time processing. For MLE products, bias corrections for different

543 observation times and surface type were performed considering pixel-level errors, and the
544 synergy of fusion between GEO satellites was successfully demonstrated.

545 Validation with the AERONET confirmed that averaging ensemble members improved
546 most of statistical metrics for ensemble products, and consideration of pixel-level uncertainty
547 further improved the accuracy of MLE products. For optimized AOD products in East Asia,
548 NDVI and time-dependent errors have been reduced. The ensemble-mean and MLE fusion
549 results show consistent results with better accuracy.

550 By comparing F1 and F4, we can see the accuracy changes depending on the number of
551 members used in the ensemble-mean. During the KORUS-AQ period, poor accuracy of each
552 member for ensemble averaging made difficult to find true features. The accuracy of F4 was
553 higher than that of F1, which shows the effect of GV1's large bias during the KORUS-AQ
554 period. On the other hand, for the EMeRGe period, the difference between F1 and F4 appears
555 small because the respective ensemble member's accuracy was better. Both near-real-time
556 products, F2 and FM2, show good accuracy, similar to other fused products. Interestingly, the
557 accuracy of F1 was worse than that of F2, but the accuracy of FM1 was better than that of
558 FM2. The reason for this appears that the long-term RMSE (in Figure 1) and Gaussian center
559 value (in Figure 3) was a better representation for the EMeRGe than for the KORUS-AQ
560 period. To minimize such errors, overall results can be improved by binning the RMSE and
561 Gaussian center value for the bias correction with respect to month and season in addition to
562 NDVI and time. Naturally, if we directly use the RMSE and Gaussian center value of each
563 campaign, the accuracy can be improved.

564 In terms of %GCOS range, satellite-derived and fused products was 33-43% and 46-54%,
565 respectively during the KORUS-AQ, indicating that the fused products have a better or
566 similar statistical score along with other validation scores such as RMSE and MBE. However,
567 the %GCOS during the EMeRGe period shows better accuracy for AMR products with 52.4%
568 than for fused products with a maximum of 47.6%. In terms of other validation indices,
569 however, such as RMSE and MBE, the fused product results represent a better validation
570 score than the AMR. For low aerosol loading case where RMSE is small and similar across
571 different products, bias correction effect was also analyzed at the Gangneung-WNU site by
572 comparing F3 and FM3.

573 As a summary, to increase the accuracy of the fused products, it is required to have either
574 high accuracy of the respective satellite product, or the consistent error characteristics with
575 respect to different parameters such as time, NDVI, etc. If either each satellite-derived AOD
576 is accurate or large numbers of ensemble members are available for compensating respective
577 error, the ensemble-mean shall be the better fusion technique. If the error characteristic is not
578 random and can be expressed as a specific function, the fused product's accuracy through the
579 MLE fusion will be increased.

580 The method applied in this study could be used for AOD fusion of GEO data, such as AMI
581 onboard GK-2A, GOCI-2 and GEMS onboard GK-2B. Furthermore, it is possible to retrieve
582 AOPs other than AOD using multi-angle and multi-channel (UV, VIS, and IR) observations
583 with GK-2A and 2B.

586 **Code and data availability.**

587
588 The aerosol products data from AHI and GOCI are available on request from the
589 corresponding author (jkim2@yonsei.ac.kr).

590 **Author contributions.**

592
593 HL, SG and JK designed the experiment. HL and SG carried out the data processing. MC, SL,
594 and YK provided support on satellite data. HL wrote the manuscript with contributions from
595 co-authors. JK reviewed and edited the article. JK and CK provided support and supervision.
596 All authors analyzed the measurement data and prepared the article with contributions from
597 all co-authors.
598

599 **Competing interests.**

600
601 The authors declare that they have no conflict of interest.
602

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615

616 **References**

617 Bernard, E., Moulin, C., Ramon, D., Jolivet, D., Riedi, J., and Nicolas, J. M.: Description and validation of an
618 AOT product over land at the 0.6 μm channel of the SEVIRI sensor onboard MSG, Atmospheric Measurement
619 Techniques, 4, 2543-2565, 2011.

620 Bessho, K., Date, K., Hayashi, M., Ikeda, A., Imai, T., Inoue, H., Kumagai, Y., Miyakawa, T., Murata, H., Ohno,
621 T., Okuyama, A., Oyama, R., Sasaki, Y., Shimazu, Y., Shimoji, K., Sumida, Y., Suzuki, M., Taniguchi, H.,
622 Tsuchiyama, H., Uesawa, D., Yokota, H., and Yoshida, R.: An Introduction to Himawari-8/9—
623 Japan's New-Generation Geostationary Meteorological Satellites, Journal of the Meteorological Society
624 of Japan. Ser. II, 94, 151-183, 2016.

625 Bilal, M., Nichol, J. E., and Wang, L.: New customized methods for improvement of the MODIS C6 Dark
626 Target and Deep Blue merged aerosol product, Remote Sensing of Environment, 197, 115-124, 2017.

627 Chatterjee, A., Michalak, A. M., Kahn, R. A., Paradise, S. R., Braverman, A. J., and Miller, C. E.: A
628 geostatistical data fusion technique for merging remote sensing and ground-based observations of aerosol
629 optical thickness, Journal of Geophysical Research, 115, 2010.

630 Cho, Hi K., Jeong, M. J., Kim, J., Kim, Y. J.: Dependence of diffuse photosynthetically active solar irradiance
631 on total optical depth, Journal of Geophysical Research, 108, D9, 4267, 4-1~4-10, 2003.

633 Choi, J.-K., Park, Y. J., Ahn, J. H., Lim, H.-S., Eom, J., and Ryu, J.-H.: GOCI, the world's first geostationary
634 ocean color observation satellite, for the monitoring of temporal variability in coastal water turbidity, Journal of
635 Geophysical Research: Oceans, 117, C9, 2012.

636 Choi, M., Kim, J., Lee, J., Kim, M., Park, Y.-J., Jeong, U., Kim, W., Hong, H., Holben, B. N., Eck, T. F., Song,
637 C. H., Lim, J.-H., and Song, C.-K.: GOCI Yonsei Aerosol Retrieval (YAER) algorithm and validation during
638 the DRAGON-NE Asia 2012 campaign, *Atmos. Meas. Tech.*, 9, 1377-1398, 2016.

639 Choi, M., Kim, J., Lee, J., Kim, M., Park, Y.-J., Holben, B., Eck, T. F., Li, Z., and Song, C. H.: GOCI Yonsei
640 aerosol retrieval version 2 products: an improved algorithm and error analysis with uncertainty estimation from
641 5-year validation over East Asia, *Atmospheric Measurement Techniques*, 11, 385-408, 2018.

642 Cox, C.: Statistics of the sea surface derived from sun glitter, *J. Marine Research*, 13, 198-227, 1954.

643 Crawford, J., J.-Y. Ahn, J. Al-Saadi, L. Chang, L. K. Emmons, J. Kim, G. Lee, J.-H. Park, R. J. Park, J. H. Woo,
644 C.-K. Song, J.-H. Hong, Y.-D. Hong, B. L. Lefer, M. Lee, T. Lee, S. Kim, K.-E. Min, S. S. Yum, H. J. Shin, Y.-
645 W. Kim, J.-S. Choi, J.-S. Park, J. J. Szykman, R. W. Long, C. E. Jordan, I. J. Simpson, A. Fried, J. E. Dibb, S.Y.
646 Cho, and Y. P. Kim: The Korea-United States Air Quality (KORUS-AQ) Field Study, *Elementa*, revised, 2021

647

648 Fukuda, S., Nakajima, T., Takenaka, H., Higurashi, A., Kikuchi, N., Nakajima, T. Y., and Ishida, H.: New
649 approaches to removing cloud shadows and evaluating the 380 nm surface reflectance for improved aerosol
650 optical thickness retrievals from the GOSAT/TANSO-Cloud and Aerosol Imager, *Journal of Geophysical
651 Research: Atmospheres*, 118, 13,520-513,531, 2013.

652 Garay, M. J., Kalashnikova, O. V., and Bull, M. A.: Development and assessment of a higher-spatial-resolution
653 (4.4 km) MISR aerosol optical depth product using AERONET-DRAGON data, *Atmospheric Chemistry and
654 Physics*, 17, 5095-5106, 2017.

655 Garay, M. J., Witek, M. L., Kahn, R. A., Seidel, F. C., Limbacher, J. A., Bull, M. A., Diner, D. J., Hansen, E. G.,
656 Kalashnikova, O. V., Lee, H., Nastan, A. M., and Yu, Y.: Introducing the 4.4 km spatial resolution
657 Multi-Angle Imaging SpectroRadiometer (MISR) aerosol product, *Atmospheric Measurement Techniques*, 13,
658 593-628, 2020.

659 GCOS, W.: Systematic Observation Requirements for Satellite-BASED Data Products for Climate, 154
660 Document. 2011.

661

662 Giles, D. M., Sinyuk, A., Sorokin, M. S., Schafer, J. S., Smirnov, A., Slutsker, I., Eck, T. F., Holben, B. N.,
663 Lewis, J., Campbell, J., Welton, E. J., Korkin, S., and Lyapustin, A.: Advancements in the Aerosol Robotic
664 Network (AERONET) Version 3 Database – Automated Near Real-Time Quality Control Algorithm with
665 Improved Cloud Screening for Sun Photometer Aerosol Optical Depth (AOD) Measurements, *Atmos. Meas.
666 Tech. Discuss.*, doi: <https://doi.org/10.5194/amt-2018-272>, 2018. 2018.

667 Go, S., Kim, J., Park, S. S., Kim, M., Lim, H., Kim, J.-Y., Lee, D.-W., and Im, J.: Synergistic Use of
668 Hyperspectral UV-Visible OMI and Broadband Meteorological Imager MODIS Data for a Merged Aerosol
669 Product, *Remote Sensing*, 12, 2020.

670

671 Gupta, P., Patadia, F., and Christopher, S. A.: Multisensor Data Product Fusion for Aerosol Research, *IEEE
672 Transactions on Geoscience and Remote Sensing*, 46, 1407-1415, 2008.

673 Gupta, P., Levy, R. C., Mattoo, S., Remer, L. A., and Munchak, L. A.: A surface reflectance scheme for
674 retrieving aerosol optical depth over urban surfaces in MODIS Dark Target retrieval algorithm, *Atmospheric
675 Measurement Techniques*, 9, 3293-3308, 2016.

676 Gupta, P., Levy, R. C., Mattoo, S., Remer, L. A., Holz, R. E., and Heidinger, A. K.: Applying the Dark Target
677 aerosol algorithm with Advanced Himawari Imager observations during the KORUS-AQ field campaign, 2019.
678 2019.

679 Herman, J., Bhartia, P., Torres, O., Hsu, C., Seftor, C., and Celarier, E.: Global distribution of UV-absorbing
680 aerosols from Nimbus 7/TOMS data, *Journal of Geophysical Research: Atmospheres*, 102, 16911-16922, 1997.

681 Holben, B. N., Tanre, D., Smirnov, A., Eck, T., Slutsker, I., Abuhamassan, N., Newcomb, W., Schafer, J., Chatenet,
682 B., and Lavenu, F. J. J. o. G. R. A.: An emerging ground-based aerosol climatology: Aerosol optical depth from
683 AERONET, 106, 12067-12097, 2001.

684 Hsu, N. C., Tsay, S.-C., King, M. D., Herman, J. R. J. I. T. o. G., and Sensing, R.: Aerosol properties over
685 bright-reflecting source regions, 42, 557-569, 2004.

686 Hsu, N., Jeong, M. J., Bettenhausen, C., Sayer, A., Hansell, R., Seftor, C., Huang, J., and Tsay, S. C.: Enhanced
687 Deep Blue aerosol retrieval algorithm: The second generation, *Journal of Geophysical Research: Atmospheres*,
688 118, 9296-9315, 2013.

689 Hsu, N., Lee, J., Sayer, A., Kim, W., Bettenhausen, C., and Tsay, S. C. J. J. o. G. R. A.: VIIRS Deep Blue
690 aerosol products over land: Extending the EOS long-term aerosol data records, 124, 4026-4053, 2019.

691 Jackson, J. M., Liu, H., Laszlo, I., Kondragunta, S., Remer, L. A., Huang, J., and Huang, H.-C.: Suomi-NPP
692 VIIRS aerosol algorithms and data products, *Journal of Geophysical Research: Atmospheres*, 118, 12,673-
693 612,689, 2013.

694 Kikuchi, M., Murakami, H., Suzuki, K., Nagao, T. M., and Higurashi, A.: Improved Hourly Estimates of
695 Aerosol Optical Thickness Using Spatiotemporal Variability Derived From Himawari-8 Geostationary Satellite,
696 *IEEE Transactions on Geoscience and Remote Sensing*, 56, 3442-3455, 2018.

697 Kim, J., Lee, J., Lee, H. C., Higurashi, A., Takemura, T., and Song, C. H., Consistency of the aerosol type
698 classification from satellite remote sensing during the Atmospheric Brown Cloud–East Asia Regional
699 Experiment campaign, *J. Geophys. Res.*, 112, D22S33, doi:10.1029/2006JD008201, 2007.

700 Kim, J., Yoon, J. M., Ahn, M. H., Sohn, B. J., and Lim, H. S.: Retrieving aerosol optical depth using visible and
701 mid-IR channels from geostationary satellite MTSAT-1R, *International Journal of Remote Sensing*, 29, 6181-
702 6192, 2008.

703 Kim, J., Kim, M., and Choi, M.: Monitoring aerosol properties in east Asia from geostationary orbit: GOCI, MI
704 and GEMS. In: *Air Pollution in Eastern Asia: An Integrated Perspective*, Springer, 2017.

705 Kim, J., Jeong, U., Ahn, M.-H., Kim, J. H., Park, R. J., Lee, H., Song, C. H., Choi, Y.-S., Lee, K.-H., Yoo, J.-M.,
706 Jeong, M.-J., Park, S. K., Lee, K.-M., Song, C.-K., Kim, S.-W., Kim, Y. J., Kim, S.-W., Kim, M., Go, S., Liu,
707 X., Chance, K., Chan Miller, C., Al-Saadi, J., Veihelmann, B., Bhartia, P. K., Torres, O., Abad, G. G., Haffner,
708 D. P., Ko, D. H., Lee, S. H., Woo, J.-H., Chong, H., Park, S. S., Nicks, D., Choi, W. J., Moon, K.-J., Cho, A.,
709 Yoon, J., Kim, S.-k., Hong, H., Lee, K., Lee, H., Lee, S., Choi, M., Veefkind, P., Levelt, P. F., Edwards, D. P.,
710 Kang, M., Eo, M., Bak, J., Baek, K., Kwon, H.-A., Yang, J., Park, J., Han, K. M., Kim, B.-R., Shin, H.-W., Choi,
711 H., Lee, E., Chong, J., Cha, Y., Koo, J.-H., Irie, H., Hayashida, S., Kasai, Y., Kanaya, Y., Liu, C., Lin, J.,
712 Crawford, J. H., Carmichael, G. R., Newchurch, M. J., Lefer, B. L., Herman, J. R., Swap, R. J., Lau, A. K. H.,
713 Kurosu, T. P., Jaross, G., Ahlers, B., Dobber, M., McElroy, C. T., and Choi, Y.: New Era of Air Quality
714 Monitoring from Space: Geostationary Environment Monitoring Spectrometer (GEMS), *Bulletin of the*
715 *American Meteorological Society*, 101, E1-E22, 2020.

716 Kim, M., Kim, J., Wong, M. S., Yoon, J., Lee, J., Wu, D., Chan, P. W., Nichol, J. E., Chung, C.-Y., and Ou, M.-
717 L.: Improvement of aerosol optical depth retrieval over Hong Kong from a geostationary meteorological satellite
718 using critical reflectance with background optical depth correction, *Remote Sensing of Environment*, 142, 176-
719 187, 2014.

720 Kim, M., Kim, J., Jeong, U., Kim, W., Hong, H., Holben, B., Eck, T. F., Lim, J. H., Song, C. K., Lee, S., and
721 Chung, C. Y.: Aerosol optical properties derived from the DRAGON-NE Asia campaign, and implications for a
722 single-channel algorithm to retrieve aerosol optical depth in spring from Meteorological Imager (MI) on-board
723 the Communication, Ocean, and Meteorological Satellite (COMS), *Atmos. Chem. Phys.*, 16, 1789-1808, 2016.

724 Kim, M., Kim, S. H., Kim, W. V., Lee, Y. G., Kim, J., and Kafatos, M. C.: Assessment of Aerosol optical depth
725 under background and polluted conditions using AERONET and VIIRS datasets, *Atmospheric Environment*,
726 245, 2021.

727 Knapp, K. R., Frouin, R., Kondragunta, S., and Prados, A.: Toward aerosol optical depth retrievals over land
728 from GOES visible radiances: determining surface reflectance, *International Journal of Remote Sensing*, 26,
729 4097-4116, 2007.

730 Koelemeijer, R., De Haan, J., and Stammes, P.: A database of spectral surface reflectivity in the range 335–772
731 nm derived from 5.5 years of GOME observations, *Journal of Geophysical Research: Atmospheres*, 108, 2003.

732 Lee, J., Kim, J., Song, C. H., Ryu, J.-H., Ahn, Y.-H., and Song, C.: Algorithm for retrieval of aerosol optical
733 properties over the ocean from the Geostationary Ocean Color Imager, *Remote Sensing of Environment*, 114,
734 1077-1088, 2010.

735 Lee, J., Kim, J., Yang, P., and Hsu, N. C.: Improvement of aerosol optical depth retrieval from MODIS spectral
736 reflectance over the global ocean using new aerosol models archived from AERONET inversion data and tri-
737 axial ellipsoidal dust database, *Atmospheric Chemistry and Physics*, 12, 7087-7102, 2012.

738 Levy, R. C., Remer, L. A., Kleidman, R. G., Mattoo, S., Ichoku, C., Kahn, R., and Eck, T. F.: Global evaluation
739 of the Collection 5 MODIS dark-target aerosol products over land, *Atmospheric Chemistry and Physics*, 10,
740 10399-10420, 2010.

741 Levy, R. C., Mattoo, S., Munchak, L. A., Remer, L. A., Sayer, A. M., Patadia, F., and Hsu, N. C.: The
742 Collection 6 MODIS aerosol products over land and ocean, *Atmospheric Measurement Techniques*, 6, 2989-
743 3034, 2013.

744 Lee, S., Kim, M., Choi, M., Go, S., Kim, J., Kim, J.-H., Lim, H.-K., Jeong, U., Goo, T.-Y., Kuze, A., Shiomi, K.,
745 and Tatsuya, Y.: Aerosol Property Retrieval Algorithm over Northeast Asia from TANSO-CAI Measurements
746 Onboard GOSAT, *Remote Sensing*, 9, 2017.

747

748 Lee, S., Kim, J., Choi, M., Hong, J., Lim, H., Eck, T. F., Holben, B. N., Ahn, J.-Y., Kim, J., and Koo, J.-H.:
749 Analysis of long-range transboundary transport (LRTT) effect on Korean aerosol pollution during the KORUS-
750 AQ campaign, *Atmospheric Environment*, 204, 53-67, 2019.

751

752 Li, L., Shi, R., Zhang, L., Zhang, J., and Gao, W.: The data fusion of aerosol optical thickness using universal
753 kriging and stepwise regression in East China, 2014, 922112.

754 Lim, H., Choi, M., Kim, M., Kim, J., and Chan, P. W.: Retrieval and Validation of Aerosol Optical Properties
755 Using Japanese Next Generation Meteorological Satellite, Himawari-8, *Korean Journal of Remote Sensing*, 32,
756 681-691, 2016.

757 Lim, H., Choi, M., Kim, J., Kasai, Y., and Chan, P.: AHI/Himawari-8 Yonsei Aerosol Retrieval (YAER):
758 Algorithm, Validation and Merged Products, *Remote Sens.*, 10, 2018.

759 Lyapustin, A., Martonchik, J., Wang, Y., Laszlo, I., and Korkin, S.: Multiangle implementation of atmospheric
760 correction (MAIAC): 1. Radiative transfer basis and look-up tables, *Journal of Geophysical Research*, 116,
761 2011a.

762 Lyapustin, A., Wang, Y., Laszlo, I., Kahn, R., Korkin, S., Remer, L., Levy, R., and Reid, J. S.: Multiangle
763 implementation of atmospheric correction (MAIAC): 2. Aerosol algorithm, *Journal of Geophysical Research*,
764 116, 2011b.

765 Lyapustin, A., Wang, Y., Korkin, S., and Huang, D.: MODIS Collection 6 MAIAC algorithm, *Atmospheric
766 Measurement Techniques*, 11, 5741-5765, 2018.

767 Mélin, F., Zibordi, G., and Djavidnia, S.: Development and validation of a technique for merging satellite
768 derived aerosol optical depth from SeaWiFS and MODIS, *Remote Sensing of Environment*, 108, 436-450, 2007.

769 Murakami, H.: Ocean color estimation by Himawari-8/AHI, 2016, 987810.

770 Negi, H. and Kokhanovsky, A. J. T. C.: Retrieval of snow albedo and grain size using reflectance measurements
771 in Himalayan basin, 5, 203, 2011.

772 Nguyen, H., Cressie, N., and Braverman, A.: Spatial Statistical Data Fusion for Remote Sensing Applications,
773 *Journal of the American Statistical Association*, 107, 1004-1018, 2012.

774 Nirala, M.: Technical Note: Multi-sensor data fusion of aerosol optical thickness, *International Journal of
775 Remote Sensing*, 29, 2127-2136, 2008.

776 Pang, J., Liu, Z., Wang, X., Bresch, J., Ban, J., Chen, D., and Kim, J.: Assimilating AOD retrievals from GOI
 777 and VIIRS to forecast surface PM2.5 episodes over Eastern China, *Atmospheric Environment*, 179, 288-304,
 778 2018.

779 Remer, L. A., Kaufman, Y., Tanré, D., Mattoo, S., Chu, D., Martins, J. V., Li, R.-R., Ichoku, C., Levy, R., and
 780 Kleidman, R.: The MODIS aerosol algorithm, products, and validation, *Journal of the atmospheric sciences*, 62,
 781 947-973, 2005.

782 Remer, L. A., Mattoo, S., Levy, R. C., and Munchak, L.: MODIS 3 km aerosol product: algorithm and global
 783 perspective, *Atmospheric Measurement Techniques Discussions*, 6, 69-112, 2013.

784 Saide, P. E., Kim, J., Song, C. H., Choi, M., Cheng, Y., and Carmichael, G. R.: Assimilation of next generation
 785 geostationary aerosol optical depth retrievals to improve air quality simulations, *Geophysical Research Letters*,
 786 41, 9188-9196, 2014.

787 Saide, P. E., Gao, M., Lu, Z., Goldberg, D., Streets, D. G., Woo, J.-H., Beyersdorf, A., Corr, C. A., Thornhill, K.
 788 L., Anderson, B., Hair, J. W., Nehrir, A. R., Diskin, G. S., Jimenez, J. L., Nault, B. A., Campuzano-Jost, P.,
 789 Dibb, J., Heim, E., Lamb, K. D., Schwarz, J. P., Perring, A. E., Kim, J., Choi, M., Holben, B., Pfister, G.,
 790 Hodzic, A., Carmichael, G. R., Emmons, L., and Crawford, J. H. : Understanding and improving model
 791 representation of aerosol optical properties for a Chinese haze event measured during KORUS-AQ,
 792 *Atmospheric Chemistry and Physics*, 20, 6455-6478, 2020.

793

794 Sayer, A., Munchak, L., Hsu, N., Levy, R., Bettenhausen, C., and Jeong, M. J.: MODIS Collection 6 aerosol
 795 products: Comparison between Aqua's e-Deep Blue, Dark Target, and "merged" data sets, and usage
 796 recommendations, *Journal of Geophysical Research: Atmospheres*, 119, 2014.

797 Sayer, A., Hsu, N., Lee, J., Bettenhausen, C., Kim, W., and Smirnov, A. J. J. o. G. R. A.: Satellite Ocean
 798 Aerosol Retrieval (SOAR) Algorithm Extension to S-NPP VIIRS as Part of the "Deep Blue" Aerosol Project,
 799 123, 380-400, 2018.

800 Sayer, A. M., Hsu, N. C., Lee, J., Kim, W. V., and Dutcher, S. T.: Validation, Stability, and Consistency of
 801 MODIS Collection 6.1 and VIIRS Version 1 Deep Blue Aerosol Data Over Land, *Journal of Geophysical
 802 Research: Atmospheres*, 124, 4658-4688, 2019.

803 Smirnov, A., Holben, B. N., Eck, T. F., Dubovik, O., and Slutsker, I.: Cloud screening and quality control
 804 algorithms for the AERONET data base, *Remote Sens. Environ.*, 73, 337-349, 2000.

805 Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, B., and
 806 Midgley, B.: *IPCC, 2013: climate change 2013: the physical science basis. Contribution of working group I to*
 807 *the fifth assessment report of the intergovernmental panel on climate change.* Cambridge University Press, 2013.

808 Tang, Q., Bo, Y., and Zhu, Y.: Spatiotemporal fusion of multiple-satellite aerosol optical depth (AOD) products
 809 using Bayesian maximum entropy method, *Journal of Geophysical Research: Atmospheres*, 121, 4034-4048,
 810 2016.

811 Wang, J.: Geostationary satellite retrievals of aerosol optical thickness during ACE-Asia, *Journal of
 812 Geophysical Research*, 108, 2003.

813 Wang, J., Brown, D. G., and Hammerling, D.: Geostatistical inverse modeling for super-resolution mapping of
 814 continuous spatial processes, *Remote Sensing of Environment*, 139, 205-215, 2013.

815 Wei, J., Li, Z., Sun, L., Peng, Y., and Wang, L.: Improved merge schemes for MODIS Collection 6.1 Dark
 816 Target and Deep Blue combined aerosol products, *Atmospheric Environment*, 202, 315-327, 2019.Xie, Y., Xue,
 817 Y., Che, Y., Guang, J., Mei, L., Voorhis, D., Fan, C., She, L., Xu, H. J. I. T. o. G., and Sensing, R.: Ensemble of
 818 ESA/AATSR aerosol optical depth products based on the likelihood estimate method with uncertainties, 56,
 819 997-1007, 2018.

820 Xu, H., Guang, J., Xue, Y., De Leeuw, G., Che, Y., Guo, J., He, X., and Wang, T. J. A. E.: A consistent aerosol
 821 optical depth (AOD) dataset over mainland China by integration of several AOD products, 114, 48-56, 2015.

822 Xue, Y., Xu, H., Mei, L., Guang, J., Guo, J., Li, Y., Hou, T., Li, C., Yang, L., He, X. J. A. C., and Discussions,
823 P.: Merging aerosol optical depth data from multiple satellite missions to view agricultural biomass burning in
824 Central and East China, 12, 10461-10492, 2012.

825

826 Yoon, J. M., Kim, J., Lee, J. H., Cho, H. K., Sohn, B.-J., and Ahn, M.-H. J. A.-P. J. o. A. S.: Retrieval of aerosol
827 optical depth over East Asia from a geostationary satellite, MTSAT-1R, 43, 49-58, 2007.

828 Yoshida, M., Kikuchi, M., Nagao, T. M., Murakami, H., Nomaki, T., and Higurashi, A.: Common Retrieval of
829 Aerosol Properties for Imaging Satellite Sensors, Journal of the Meteorological Society of Japan. Ser. II, 96B,
830 193-209, 2018.

831 Zhong, G., Wang, X., Tani, H., Guo, M., Chittenden, A., Yin, S., Sun, Z., and Matsumura, S.: A Modified
832 Aerosol Free Vegetation Index Algorithm for Aerosol Optical Depth Retrieval Using GOSAT TANSO-CAI
833 Data, Remote Sensing, 8, 2016.

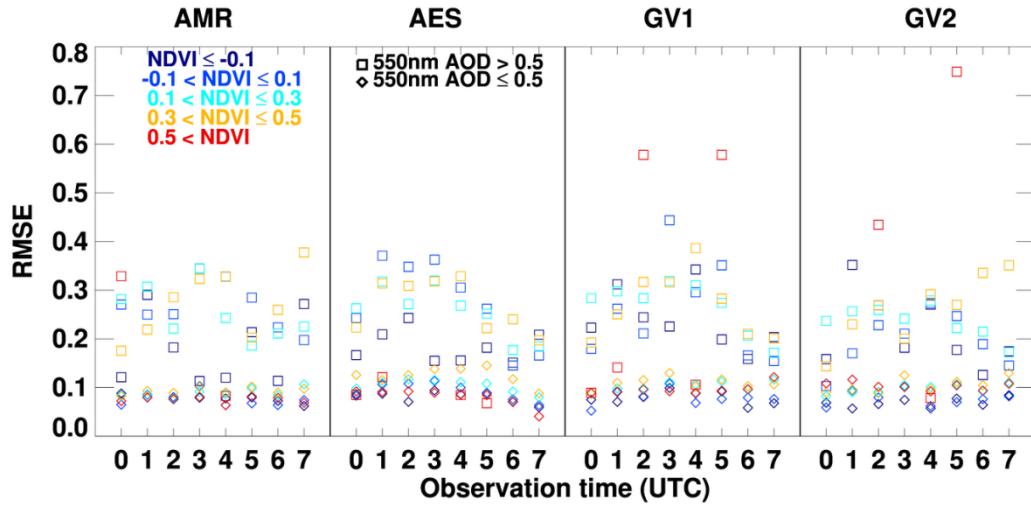
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835 Table 1. Satellite dataset used for the fusion products. Four entries F1-F4, and three entries FM1-FM3 represent
 836 ensemble-mean fusion and MLE fusion products.

AOD type	F1	F2	F3	F4	FM1	FM2	FM3
AER	o	o	o	o	o	o	o
AMR	o		o	o	o		o
GV1	o				o		
GV2	o	o		o	o	o	
Remark	All available products	For NRT ¹	AHI only for wider area	Without GV1 to check missing effect	MLE Products ²		
					Same as F1	Same as F2	Same as F3

837 ¹ NRT: near real time; ² Maximum Likelihood Estimation
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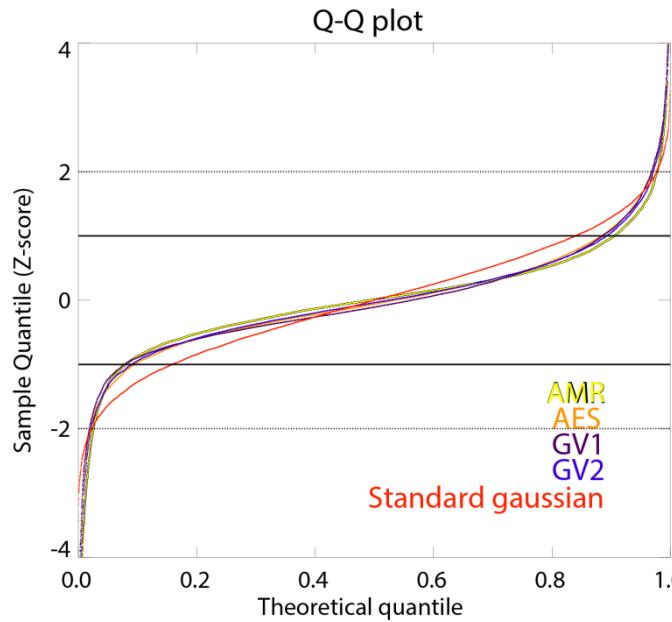
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843 Figure 1. RMSE according to NDVI (color), observation time, and satellite AODs (square and diamond
844 represent AOD at 550nm greater and less equal than 0.5) during Apr. 2018 to Mar. 2019 excluding EMeRGe
845 campaign.

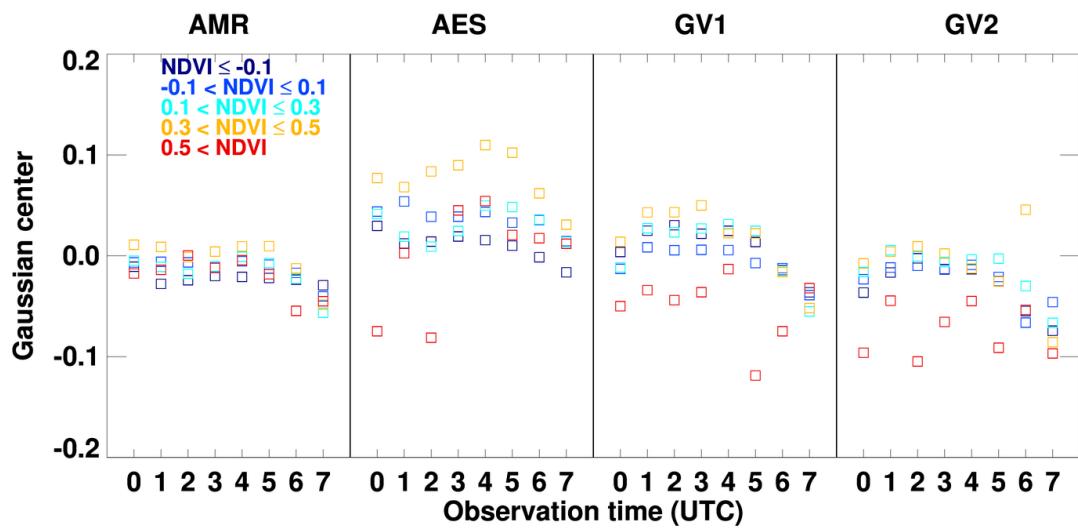
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849 Figure 2. Q-Q plot for the difference between AERONET AOD and AMR(purple), AES(cyan), GV1(green), and
850 GV2(orange) AOD. The black solid line and dotted line represent 1- σ and 2- σ , respectively.

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853 Figure 3. Systematic bias-correction values for NDVI groups and temporal bins for each satellite product from
854 Gaussian fitting analysis used in MLE fusion.

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Table 2. Validation statistics of the respective satellite product during the KORUS-AQ and the EMeRGe campaign.

Product type	KORUS-AQ					EMeRGe				
	%EE	%GCOS	RMSE	MBE	N	%EE	%GCOS	RMSE	MBE	N
AES	63.5	43.6	0.145	0.029	5069	65.2	46.3	0.176	-0.011	1884
AMR	60.6	39.4	0.150	-0.054	5069	69.4	52.4	0.162	-0.028	1884
GV1	52.2	34.7	0.153	-0.045	4843	63.4	42.7	0.162	-0.035	1760
GV2	50.3	33.8	0.176	0.008	4924	61.5	41.8	0.164	-0.001	1863

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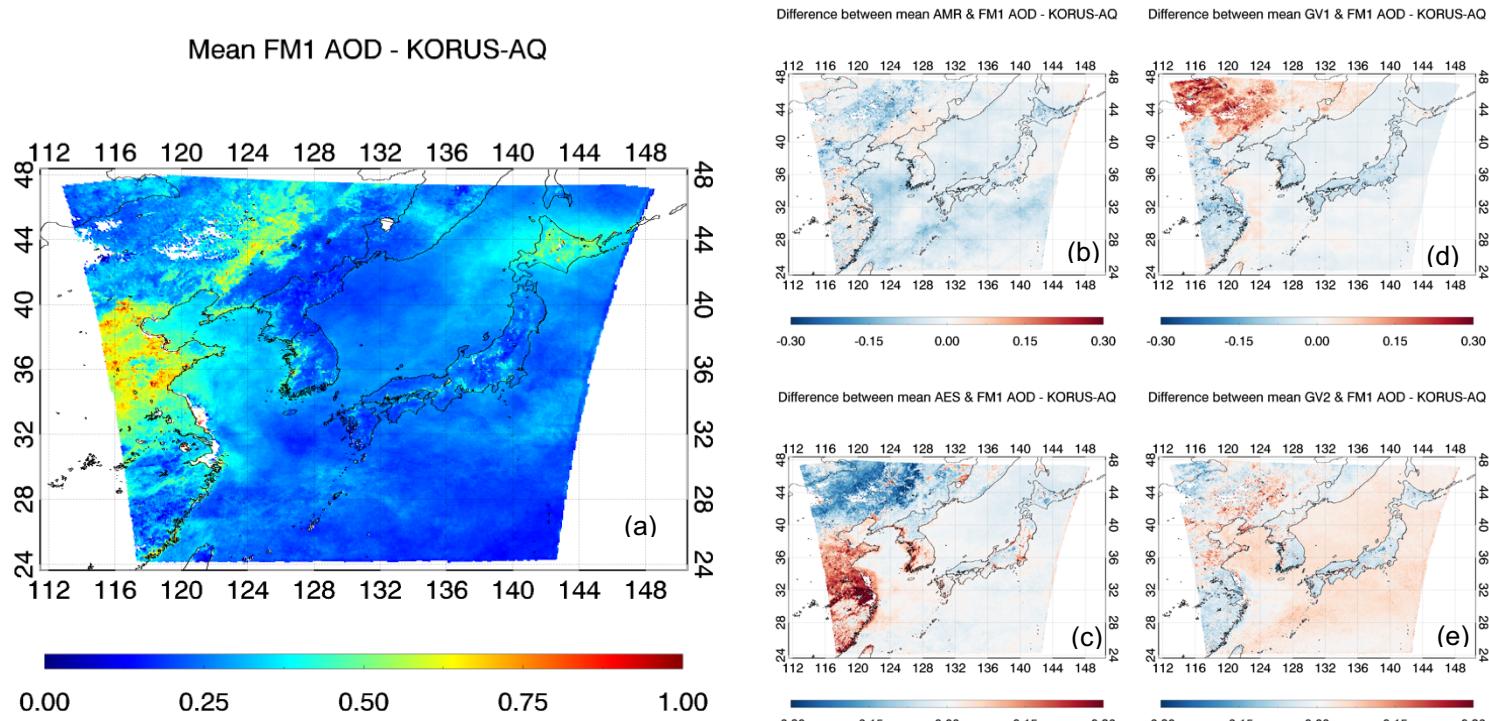


Figure 4. The average AOD of (a) FM1 (AMR, AES, GV1, and GV2) during the KORUS AQ. The difference of mean (b)AMR, (c)AES, (d)GV1, and (e)GV2 AODs with respect to mean representative (FM1) AOD. Figures generated with Interactive Data Language (IDL) version 8.8.0.

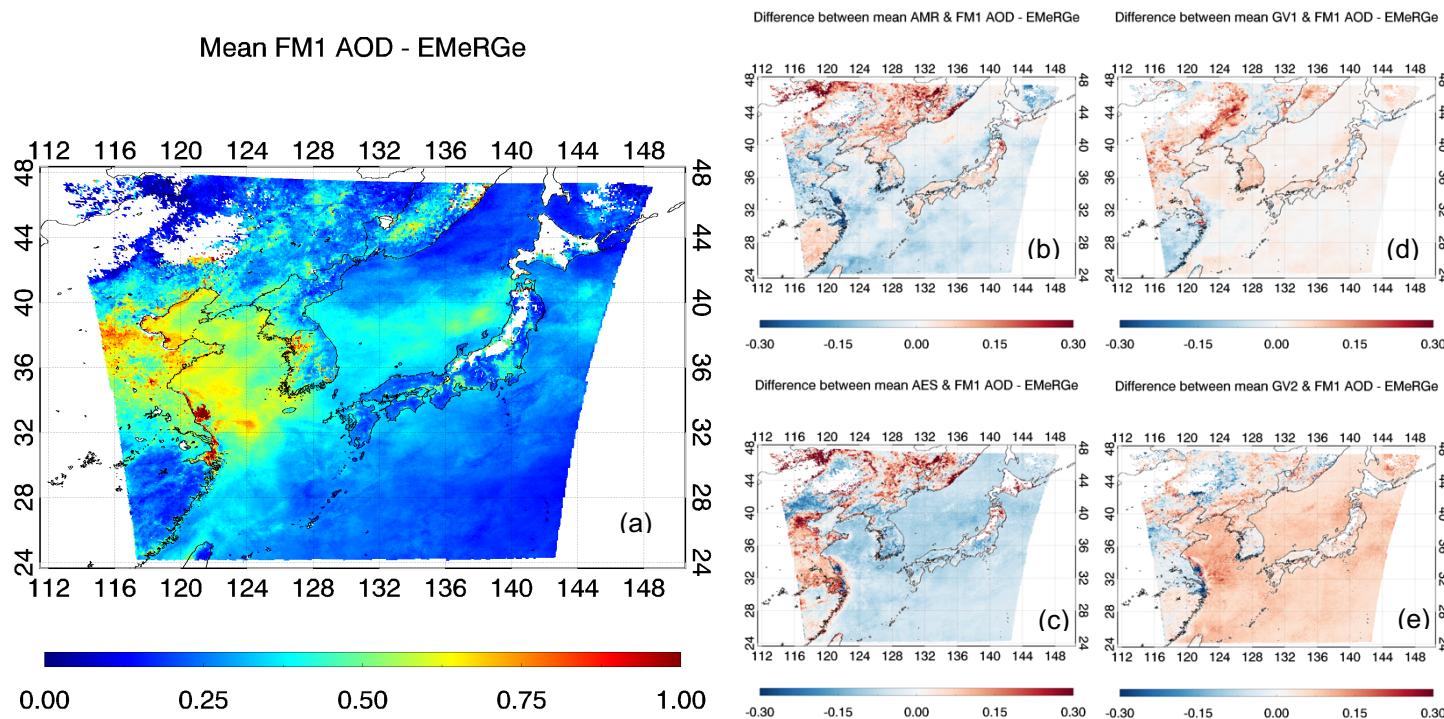


Figure 5. Same as Figure 4, but for EMeRGe campaign.

Table 3. Validation statistics of the ensemble-mean fusion (F1-F4), and MLE fusion (FM1-FM4) AOD during two field campaigns (left: KORUS-AQ, right: EMeRGe).

Fusion method	Product type	KORUS-AQ					EMeRGe				
		%EE	%GCOS	RMSE	MBE	N	%EE	%GCOS	RMSE	MBE	N
Ensemble-mean	F1	67.8	47.2	0.134	-0.014	4806	66.8	45.4	0.149	-0.012	1754
	F2	72.3	52.7	0.129	0.008	4843	66.9	45.5	0.150	-0.012	1760
	F3	72.1	51.1	0.133	0.012	5069	63.2	44.5	0.175	-0.019	1884
	F4	73.3	51.6	0.128	-0.015	4843	66.4	44.8	0.153	-0.024	1760
MLE	FM1	72.6	52.4	0.130	-0.012	4806	69.1	47.6	0.147	-0.008	1754
	FM2	65.5	46.1	0.146	0.034	4924	67.3	46.5	0.152	0.014	1863
	FM3	75.2	54.5	0.129	-0.09	5069	62.4	41.8	0.177	-0.027	1884

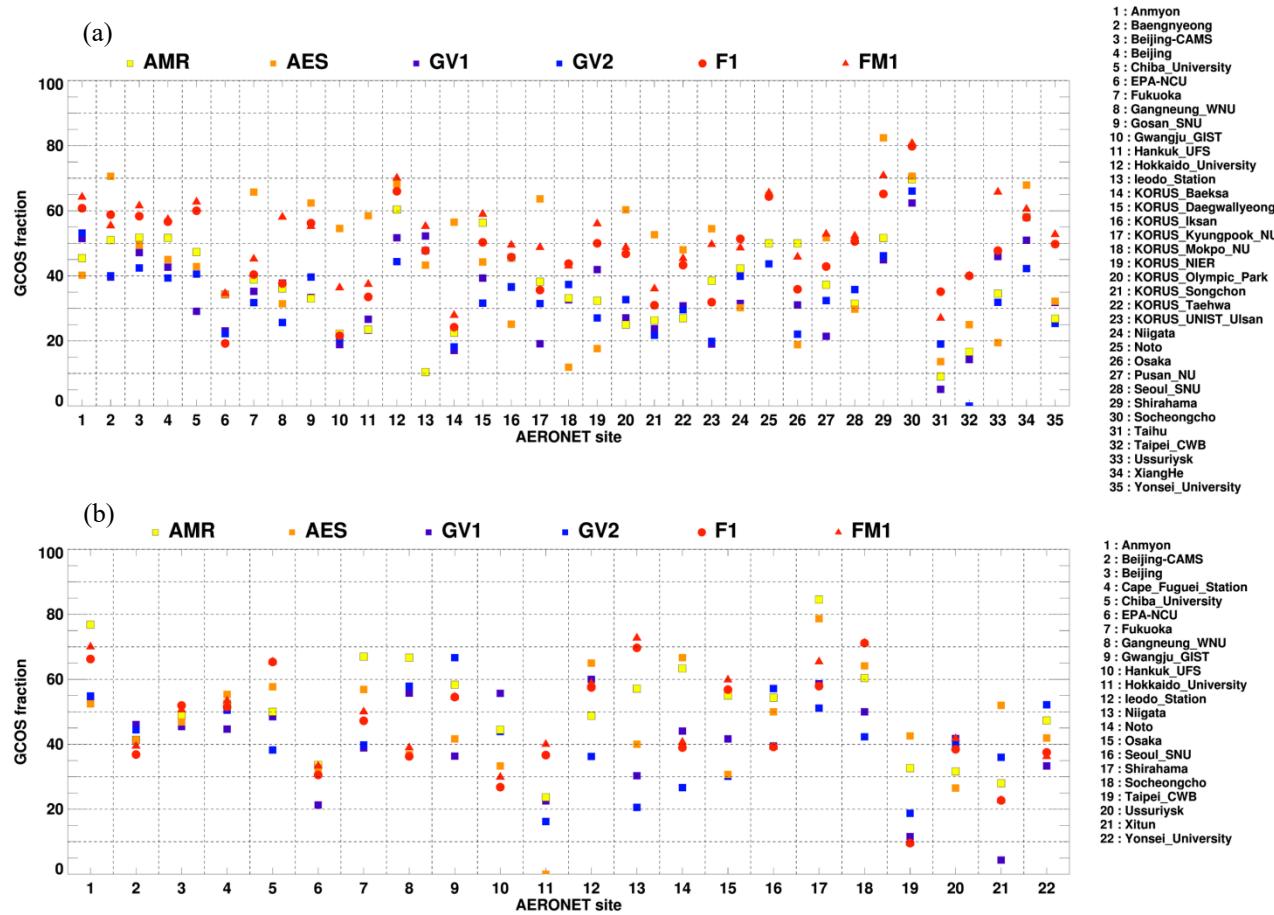


Figure 6. Comparison of the GCOS fraction for respective satellite (AMR, AES, GV1, and GV2), ensemble-mean fusion (F1), and MLE fusion (FM1) during the (a) KORUS-AQ and (b) EMeRGe campaign.

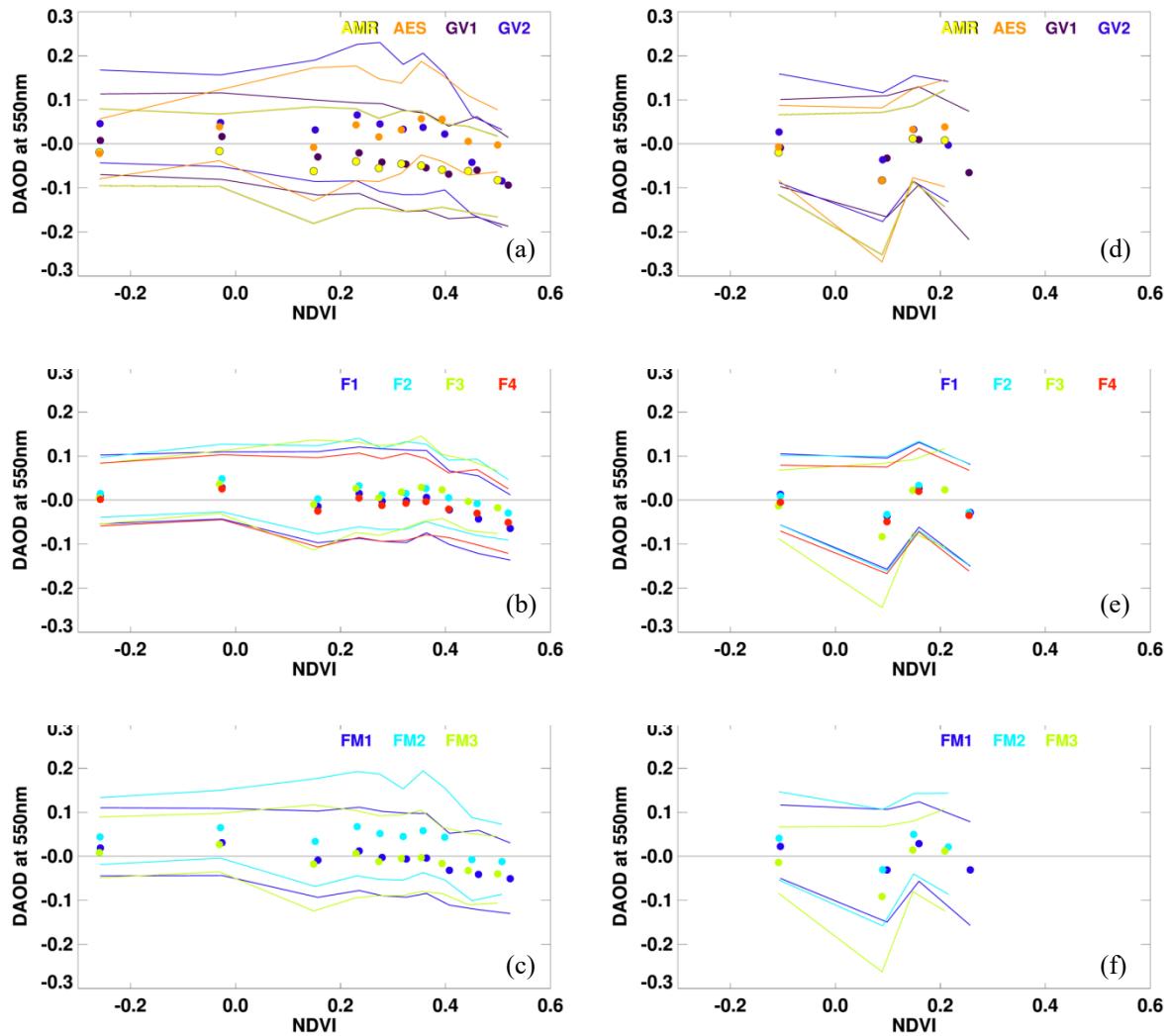


Figure 7. Difference between (a, d) respective, (b, e) ensemble-mean, or (c, f) MLE and AERONET AOD in terms of NDVI during the KORUS-AQ (left column) and the EMeRGe (right column) campaigns. Each points and solid lines represent the median and 1- σ (16th and 84th percentile) of 500 (for the KORUS-AQ) and 400 (for the EMeRGe) collocated data points in terms of NDVI values.

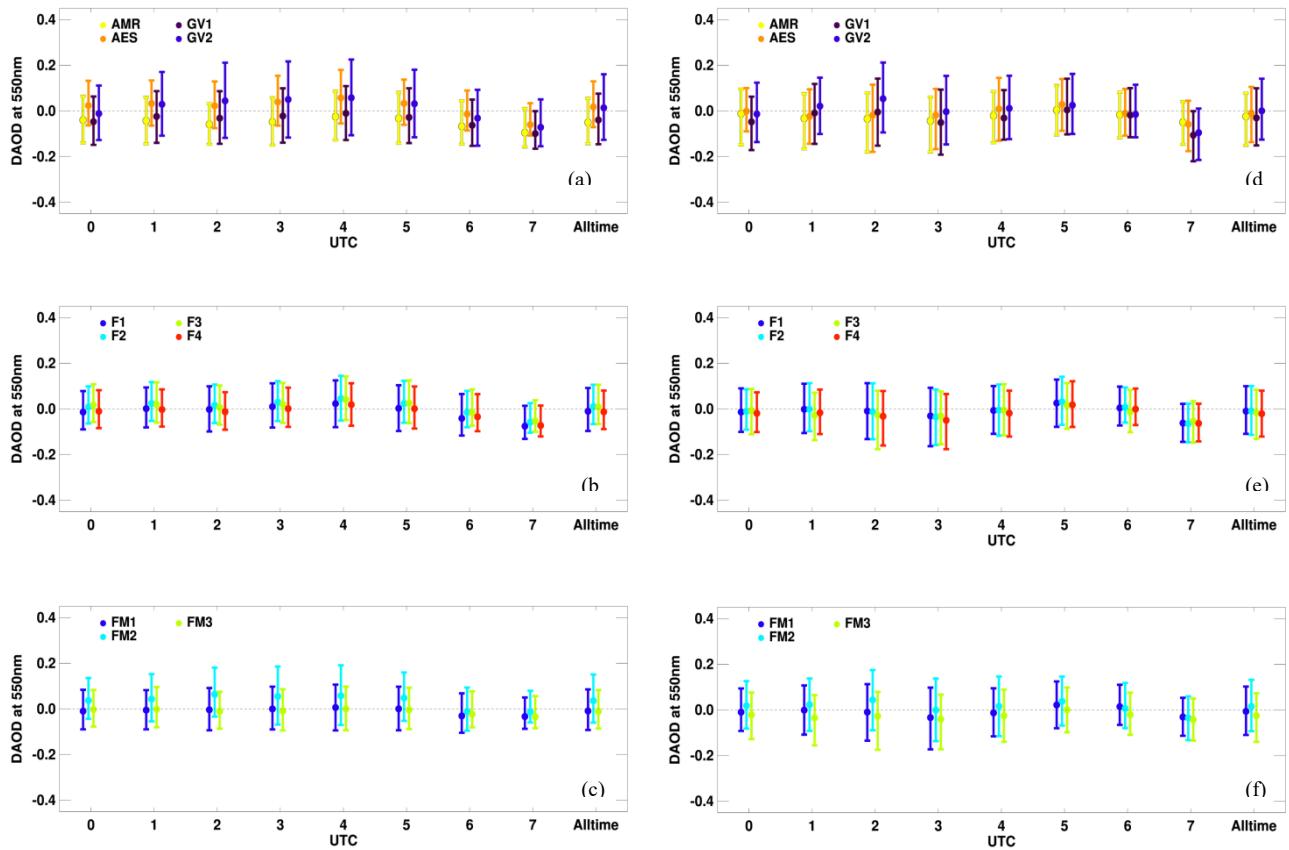


Figure 8. Same as Figure8, but for the observation time.

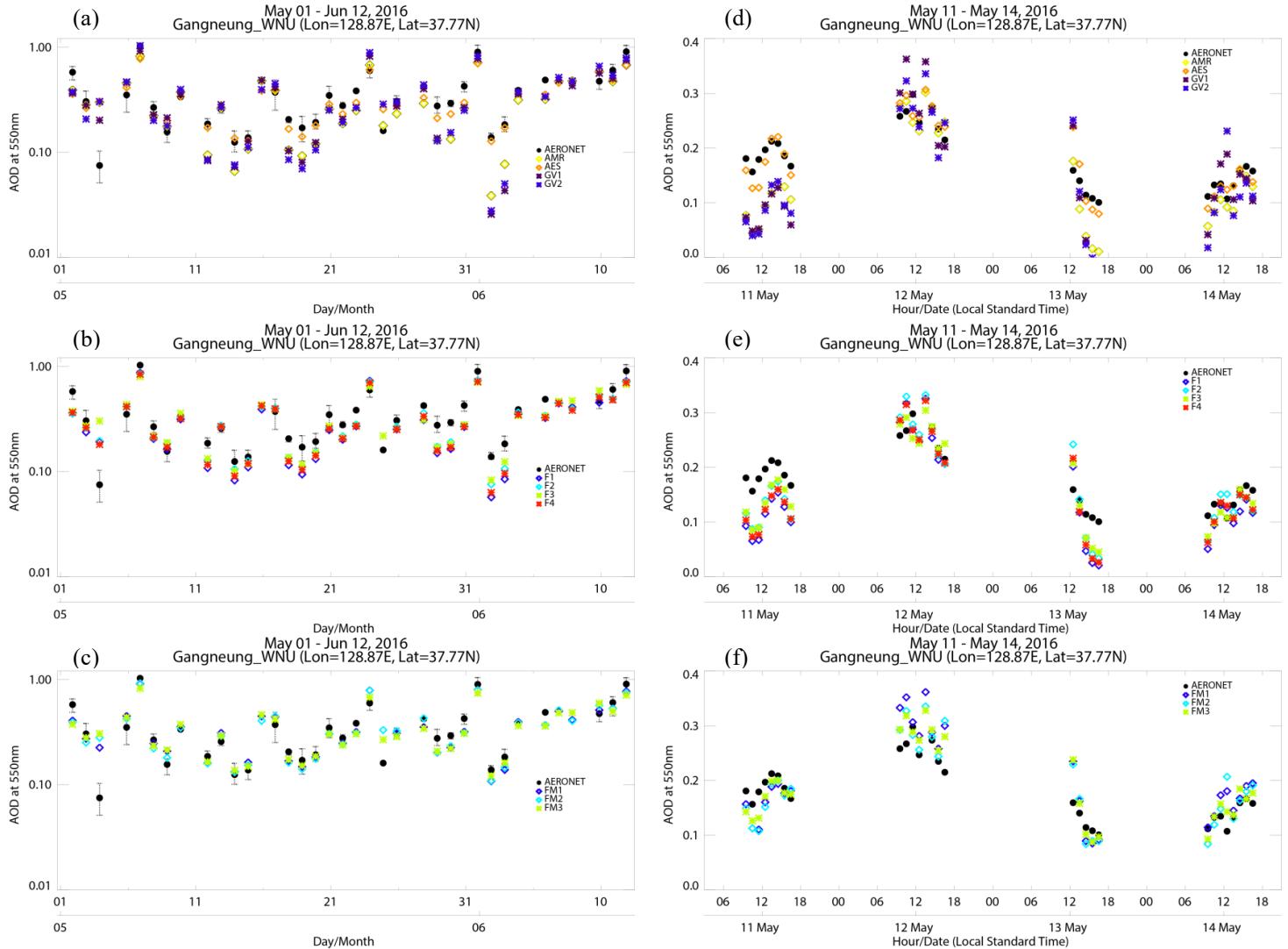


Figure 9. Time series of the daily average AODs at Gangneung WNU site during the KORUS-AQ campaign from (a) respective satellite, (b) ensemble-mean, and (c) MLE fusion. The black-filled circle represents AERONET AOD, and the error bar represents 1-SD of daily AERONET AODs. The diurnal variation in AODs from 11 to 14 May 2016 is shown in the right column, where (d) is the respective satellite, (e) is fused, and (f) is MLE products.

Table 4. Accuracy evaluation of outside of GOCI area of AMR, AES, F3, and FM3 AODs.

Without GOCI domain	KORUS- AQ AMR	KORUS- AQ AES	KORUS- AQ F3	KORUS- AQ FM3	EMeRGe AMR	EMeRGe AES	EMeRGe F3	EMeRGe FM3
N	1959	1958	1958	1958	2610	2610	2610	2610
R	0.699	0.658	0.713	0.707	0.794	0.826	0.829	0.821
RMSE	0.238	0.305	0.225	0.223	0.278	0.233	0.269	0.279
MBE	-0.098	0.130	0.041	0.015	-0.135	-0.055	-0.145	-0.158
GCOS	25.6	25.6	27.3	26.5	26.8	34.1	29.0	27.5