

# Integration of GOCI and AHI Yonsei Aerosol Optical Depth Products During the 2016 KORUS-AQ and 2018 EMeRGe Campaigns

Hyunkwang Lim<sup>1</sup>, Sujung Go<sup>1,2</sup>, Jhoon Kim<sup>1</sup>, Myungje Choi<sup>2,3</sup>, Seoyoung Lee<sup>1</sup>, Chang-Keun Song<sup>4</sup>, Yasuko Kasai<sup>5</sup>

<sup>1</sup>Department of Atmospheric Sciences, Yonsei University, Seoul 03722, Republic of Korea

<sup>2</sup>Joint Center for Earth Systems Technology, University of Maryland Baltimore County, Baltimore, MD, USA

<sup>3</sup>Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA

<sup>4</sup>School of Urban and Environmental Engineering, Ulsan National Institute of Science and Technology, Ulsan 44919, Republic of Korea

<sup>5</sup>Natinal Institute of Information and Communications Technology, Tokyo 184-8759, Japan

*Correspondence to:* Jhoon Kim (jkim2@yonsei.ac.kr)

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

## 1. Introduction

Aerosols are generated by human activities and natural processes on local to global scales, and have a lifetime of several to tens of days. Aerosols affect Earth's radiative energy balance by scattering and absorption (e.g. Cho et al., 2003). High aerosol loadings are persistent in Northeast Asia, including diverse aerosol types from various sources. Interactions among aerosols, clouds, and radiation in the atmosphere cause significant uncertainties in climate-model calculations (IPCC, 2013). Datasets produced by satellites have been widely used to 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  $\mu\text{m}$  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  $10\text{ km} \times 10\text{ km}$  and  $3\text{ km} \times 3\text{ km}$   
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

92 AOPs other than aerosol optical depth (AOD) (Wang et al., 2003; Knapp et al., 2005; Kim et  
93 al., 2008, 2014, 2016; Bernard et al., 2011). However, the Geostationary Ocean Color Imager  
94 (GOCI) onboard the GK-1 satellite, also known as the Communication, Ocean, and  
95 Meteorological Satellite (COMS), has six VIS and two near-infrared (NIR) channels, which  
96 is advantageous for retrieving AOPs (Lee et al., 2010; Choi et al., 2016, 2018; Kim et al.,  
97 2017). Next-generation meteorological GEO satellite instruments, including the Advanced  
98 Himawari Imager (AHI), Advanced Baseline Imager (ABI), and Advanced Meteorological  
99 Imager (AMI), have three to four VIS and NIR channels, which enable aerosol property  
100 retrieval with high accuracy (Lim et al., 2016, 2018; Kikuchi et al., 2018; Yoshida et al.,  
101 2018; Gupta et al., 2019). Kikuchi et al. (2018) and Yoshida et al. (2018) performed aerosol  
102 retrievals using the MRM and corrected reflectance using empirical equations. Gupta et al.  
103 (2019) extended the MODIS DT algorithm to GEO satellites and estimated visible surface  
104 reflectance using SWIR reflectance. Lim et al. (2018) retrieved the AOPs using both MRM  
105 and estimated surface reflectance from short-wave IR (SWIR) data (ESR), and presented the  
106 two merged products: an L2-AOD merged product, and a reprocessed AOD produced by  
107 merging MRM and ESR surface reflectances. The MRM gives better accuracy over brighter  
108 surfaces such as urban areas, while the ESR method gives better accuracy over areas of dense  
109 vegetation (Lim et al., 2018). However, there is a critical surface reflectance at which aerosol  
110 signals disappear, depending on the single-scattering albedo (Kim et al., 2016). Over the  
111 ocean, both the MRM and ESR methods give high accuracy, but ESR results are robust with  
112 the Cox and Munk model.

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

129  
130 Algorithms developed to date for LEO and GEO satellites have both advantages and  
131 disadvantages, depending on algorithm characteristics. Therefore, the MODIS team provides  
132 combined DT and DB AOD products (Levy et al., 2013; Sayer et al., 2014). In addition,  
133 several studies of the fusion of L2 products have been conducted (Levy et al., 2013; Sayer et  
134 al., 2014; Wei et al., 2019), with Bilal et al. (2017) obtaining reliable results from merged DT  
135 and DB products, as indicated by the NDVI in East Asia, and also robust products by simply  
136 averaging DT and DB without consideration of the NDVI.

137 AOP data fusion in East Asia may also be achieved using aerosol products of AMI, GOCI-2,  
138 and the geostationary environment monitoring spectrometer (GEMS) onboard the GK-2A and  
139 2B satellites launched by South Korea in 2018 and 2020, respectively, with accuracy over  
140 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  $\mu\text{m}$  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 μm 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<sup>-3</sup> 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  $128.2^\circ \text{ E}$  and  $140.7^\circ \text{ E}$ , 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  $\tau_i^{MLE}$  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.  
322

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

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

347 Table 2 shows the validation metrics of the respective product during the two field  
348 campaigns. The collocation points for validation with AERONET of two AHI and two GOCI  
349 products were not significantly different. %EE and %GCOS of AES and AMR showed better  
350 accuracy than GV1 and GV2 during the KORUS and the EMeRGe periods. In terms of MBE,  
351 GV2 is 0.008 and -0.001, which shows during the KORUS-AQ and the EMeRGe periods  
352 close to zero. Additionally, further analyzes of the respective satellite product are carried out  
353 along with fused products in Section 5.  
354

## 355 4. Results

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



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

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

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

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

390

## 391 **5. Validation, comparison, and error estimation against AERONET**

### 392 **5.1 Validation for fused AOD products with AERONET**

393

394 The spatio-temporal matching method between fused AOD and AERONET was performed  
395 as mentioned above in Section 3.5, and the statistics indices used for verification are also the  
396 same. Validation indices of fused products with AERONET AOD during the two campaign  
397 periods are summarized in Table 3. During the KORUS-AQ, fused AODs have better  
398 accuracy of than respective satellite product in terms of %EE and %GCOS. The %EE  
399 and %GCOS of AES, which showed the best accuracy among the respective product, are 63.5%  
400 and 43.6%, which are poor than the worst accuracy of the fused AOD. All RMSE has been  
401 improved except for FM2. The RMSE of FM2 is higher than RMSE of respective satellite  
402 product by 0.001. Although all MBEs show different patterns, the deviation of the fused  
403 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.  
414

## 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  $\pm 1$  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  $\pm 1$  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  $\pm 1$  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  $\pm 1$  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  $\text{AOD} \leq 0.5$ . 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  $\mu\text{m}$  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.

584  
585

#### 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](mailto:jkim2@yonsei.ac.kr)).

590

#### 591 **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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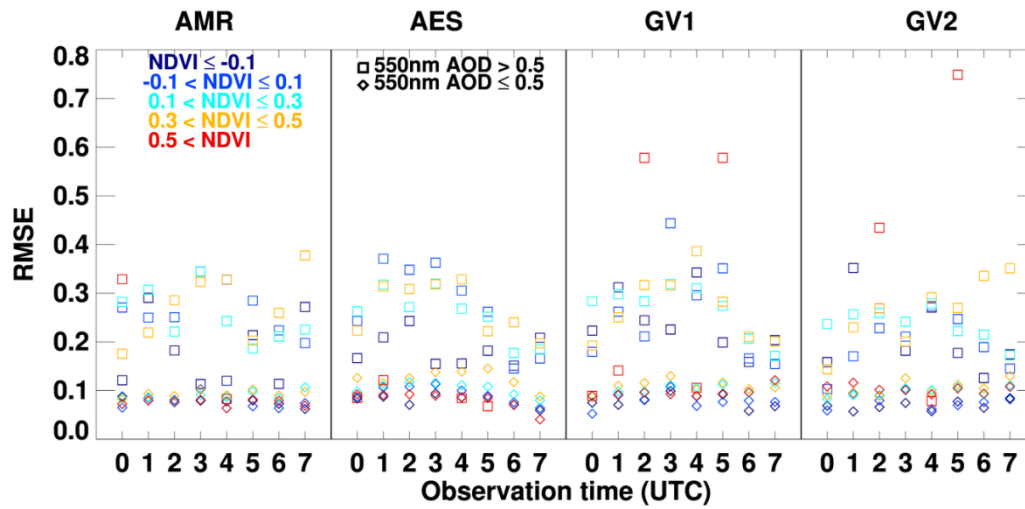
835 Table 1. Satellite dataset used for the fusion products. Four entries F1-F4, and three entries FM1-FM3 represent  
 836 ensemble-mean fusion and MLE fusion products.

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				Without GV1 to check missing effect	MLE Products <sup>2</sup>		
	All available products	For NRT <sup>1</sup>	AHI only for wider area		Same as F1	Same as F2	Same as F3

837 <sup>1</sup> NRT: near real time; <sup>2</sup> Maximum Likelihood Estimation

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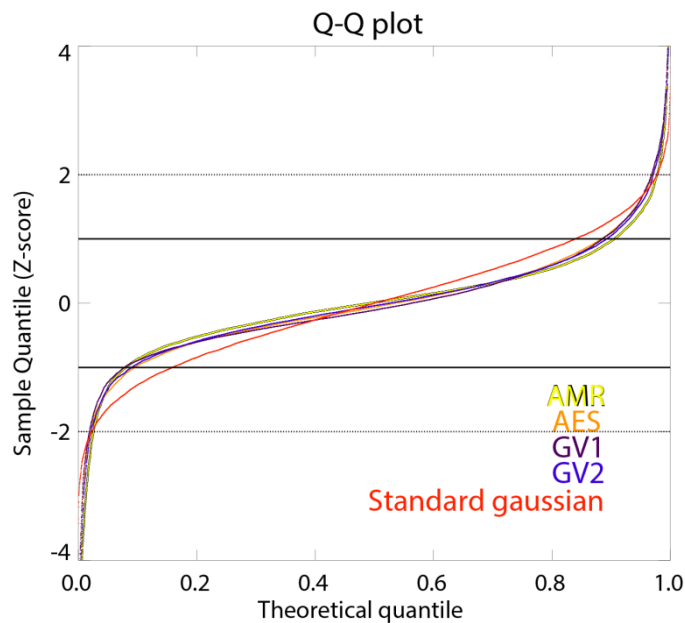
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Figure 1. RMSE according to NDVI (color), observation time, and satellite AODs (square and diamond represent AOD at 550nm greater and less equal than 0.5) during Apr. 2018 to Mar. 2019 excluding EMeRGe campaign.

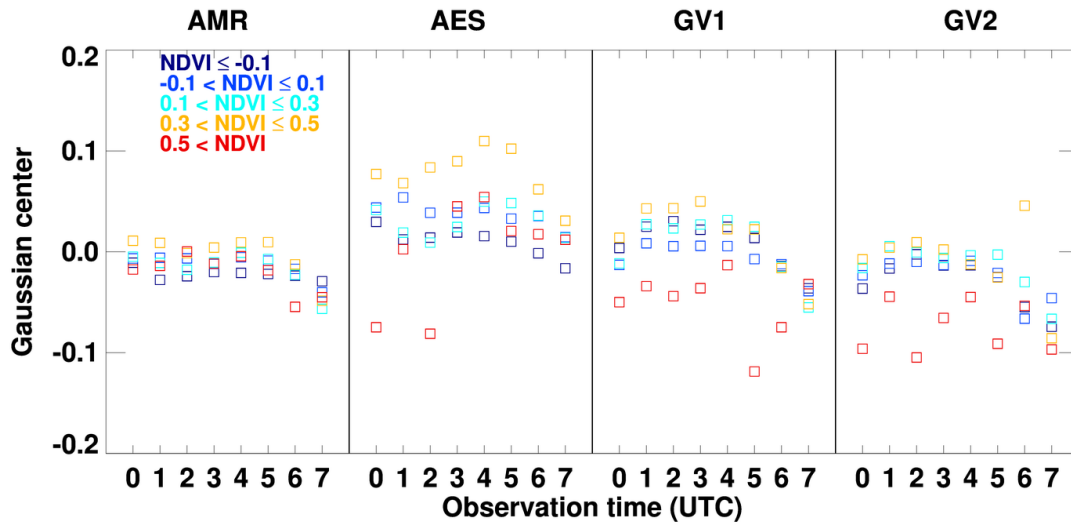
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Figure 2. Q-Q plot for the difference between AERONET AOD and AMR(purple), AES(cyan), GV1(green), and GV2(orange) AOD. The black solid line and dotted line represent 1- $\sigma$  and 2- $\sigma$ , respectively.

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

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

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

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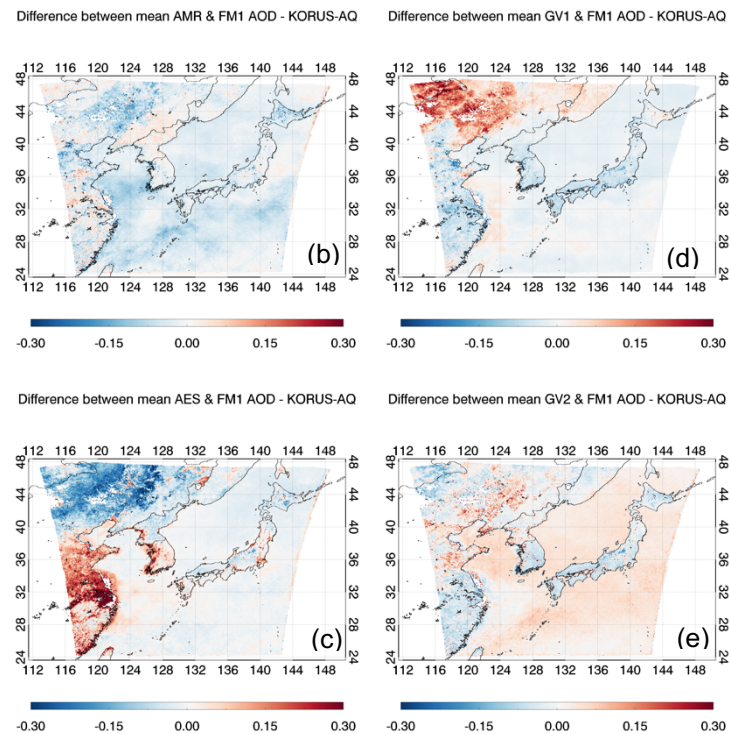
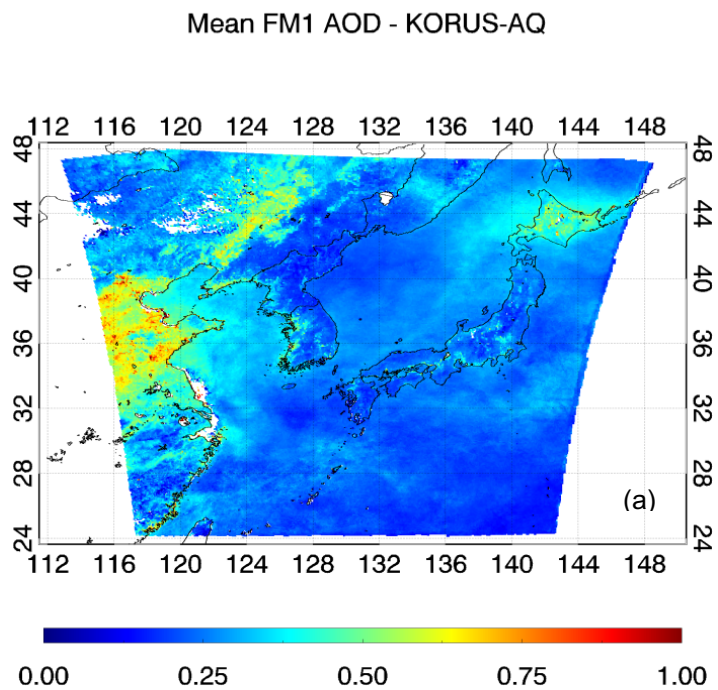


Figure 4. The average AOD of (a) FM1 (AMR, AES, GV1, and GV2) during the KORUS AQ. The difference of mean (b)AMR, (c)AES, (d)GV1, and (e)GV2 AODs with respect to mean representative (FM1) AOD. Figures generated with Interactive Data Language (IDL) version 8.8.0.



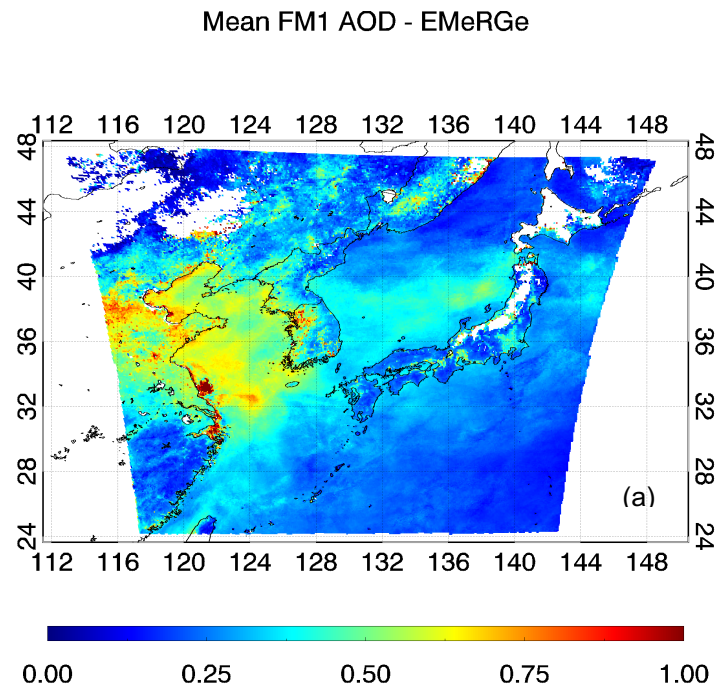


Figure 5. Same as Figure 4, but for EMeRGe campaign.

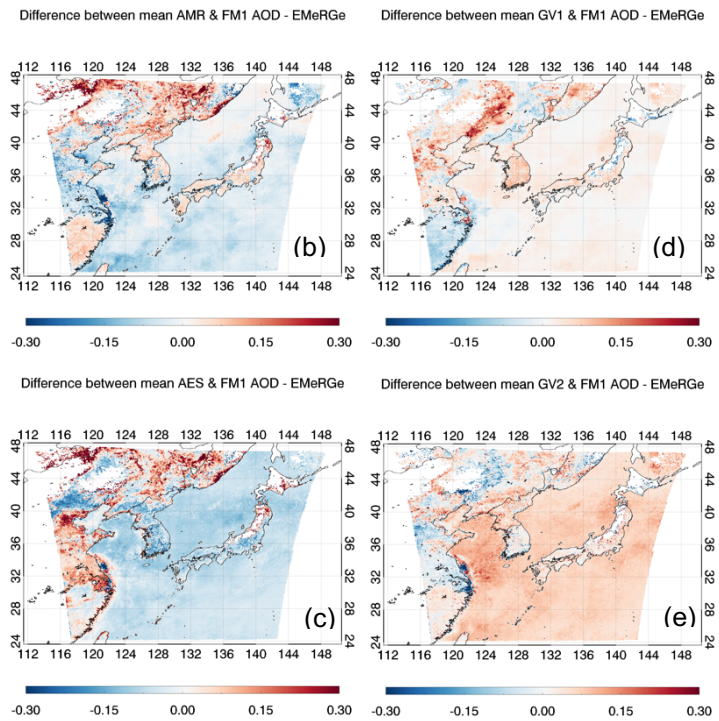


Table 3. Validation statistics of the ensemble-mean fusion (F1-F4), and MLE fusion (FM1-FM4) AOD during two field campaigns (left: KORUS-AQ, right: EMeRGe).

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

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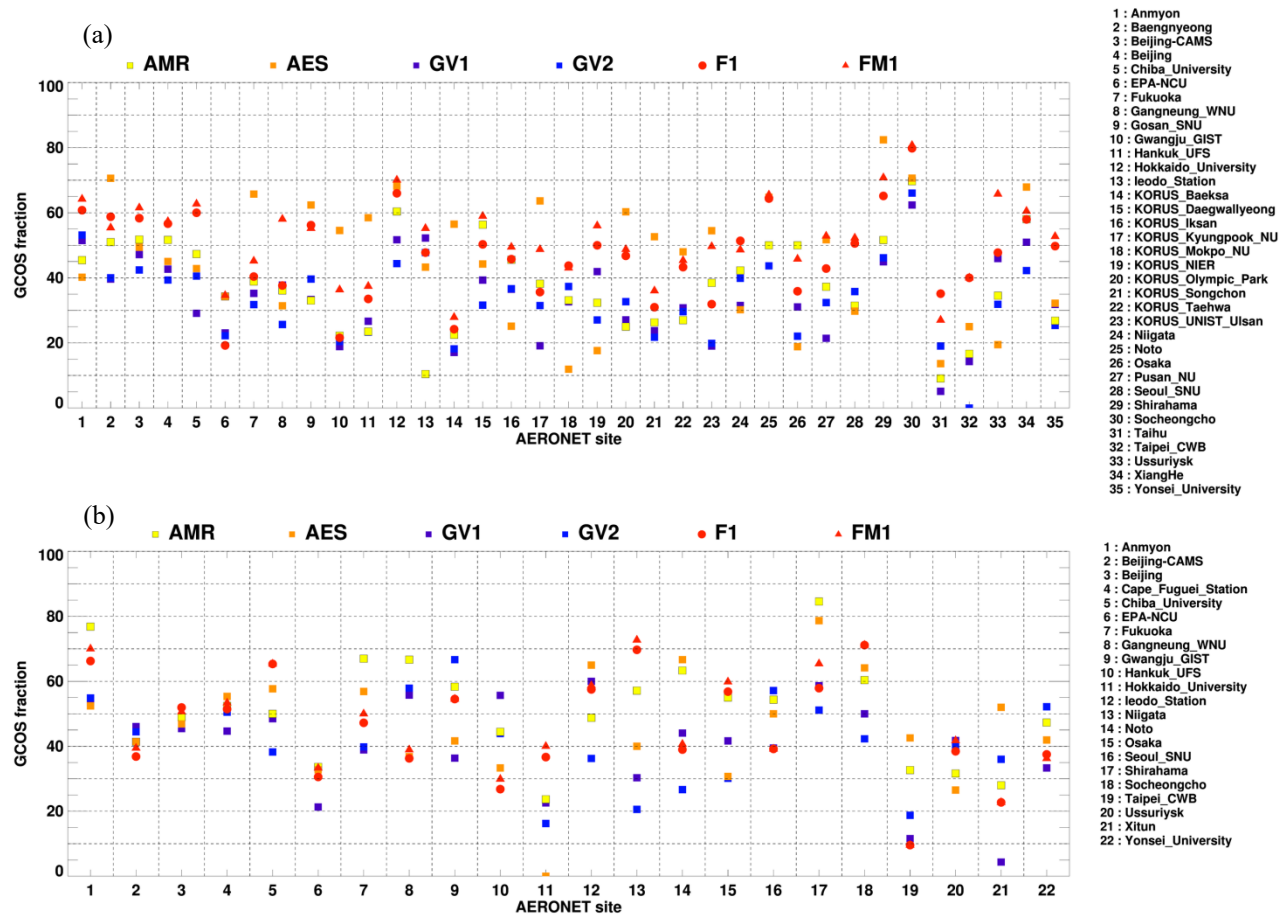


Figure 6. Comparison of the GCOS fraction for respective satellite (AMR, AES, GV1, and GV2), ensemble-mean fusion (F1), and MLE fusion (FM1) during the (a) KORUS-AQ and (b) EMERGE campaign.

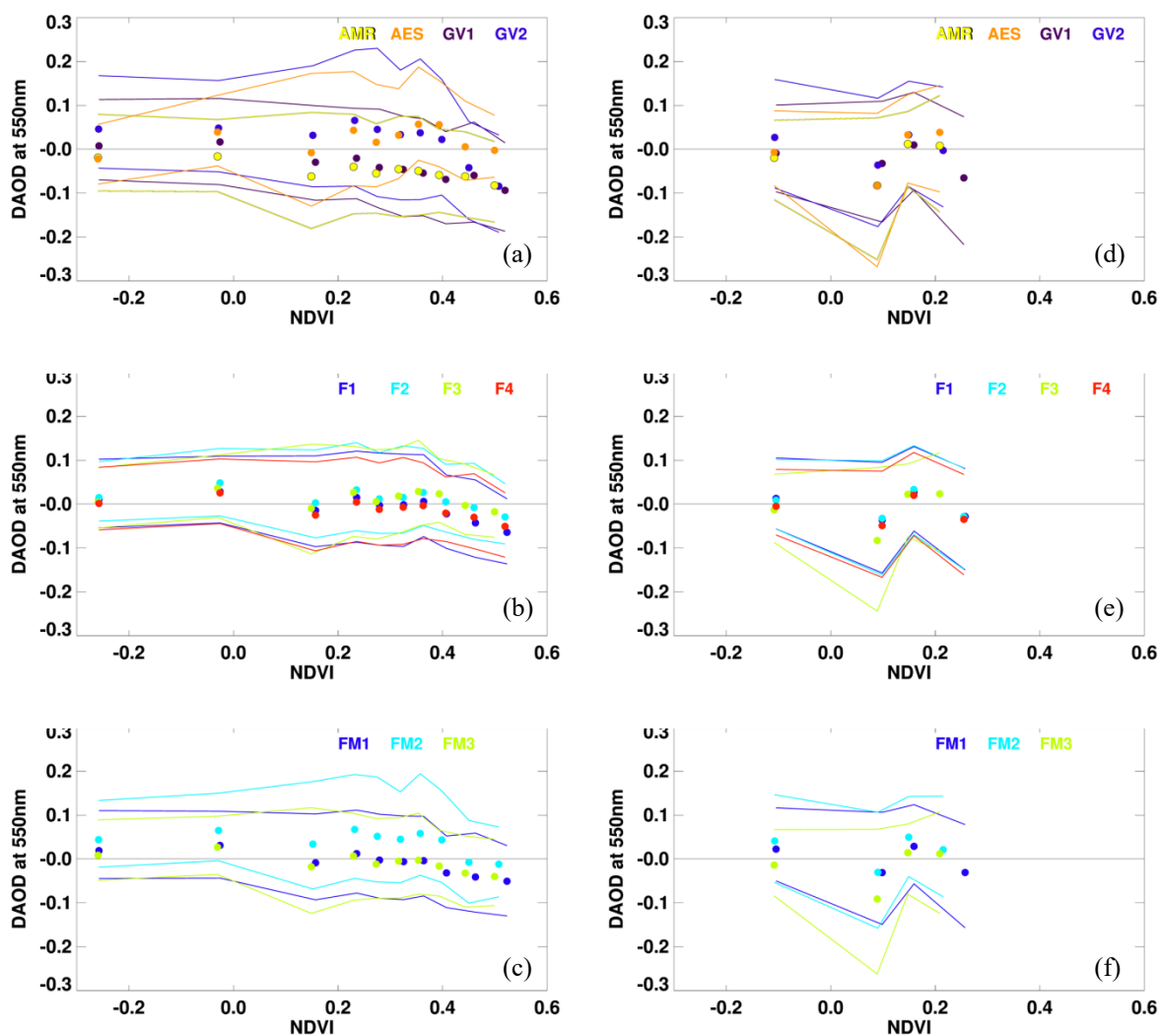


Figure 7. Difference between (a, d) respective, (b, e) ensemble-mean, or (c, f) MLE and AERONET AOD in terms of NDVI during the KORUS-AQ (left column) and the EMERG (right column) campaigns. Each points and solid lines represent the median and 1- $\sigma$  (16<sup>th</sup> and 84<sup>th</sup> percentile)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

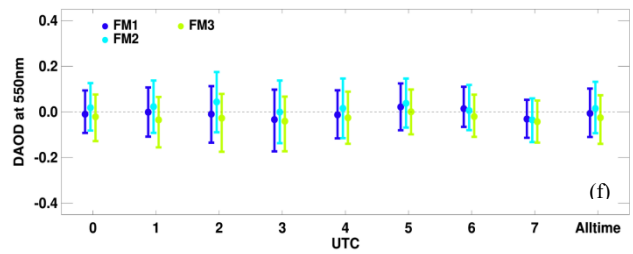
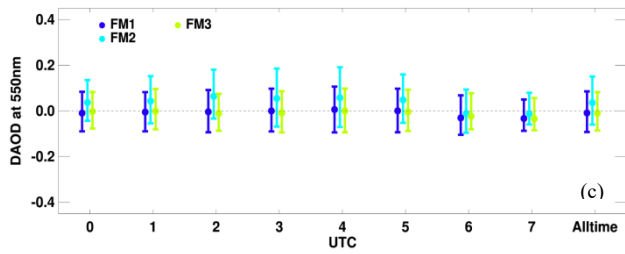
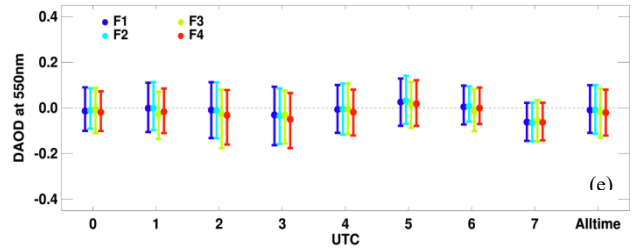
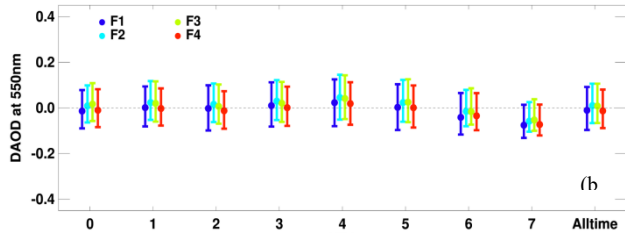
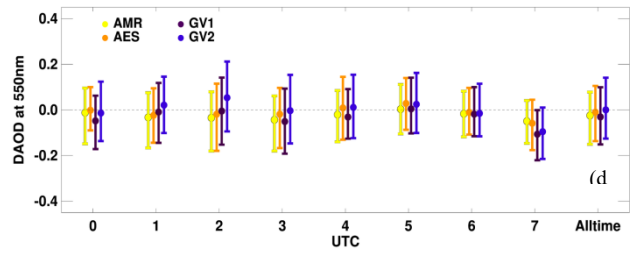
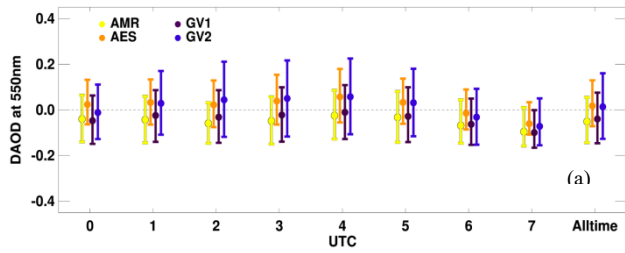


Figure 8. Same as Figure8, but for the observation time.

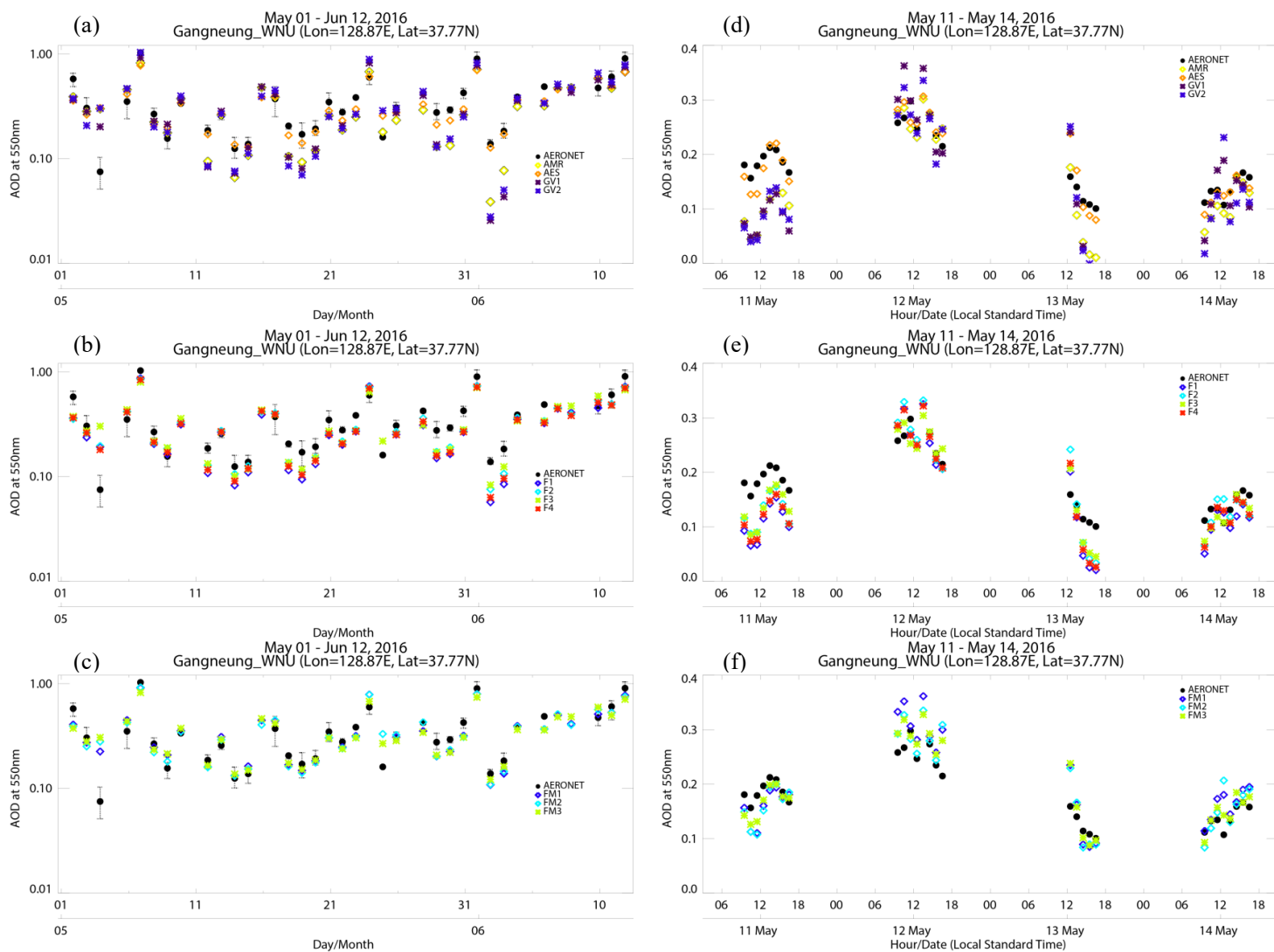


Figure 9. Time series of the daily average AODs at Gangneung WNU site during the KORUS-AQ campaign from (a) respective satellite, (b) ensemble-mean, and (c) MLE fusion. The black-filled circle represents AERONET AOD, and the error bar represents 1-SD of daily AERONET AODs. The diurnal variation in AODs 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