

1 Retrieval of cloud properties from spectral zenith radiances 2 observed by sky radiometers

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13
14 **Abstract:** An optimal estimation algorithm to retrieve cloud optical depth (COD) and cloud particle effective radius
15 (CER) from spectral zenith radiances observed by narrow field-of-view (FOV) ground-based sky radiometers is
16 developed. To further address the filter degradation problem while analyzing long-term observation data, an on-site
17 calibration procedure is proposed, which has good accuracy compared with the standard calibration transfer method. An
18 error evaluation study conducted by assuming errors in observed transmittances and ancillary data for water vapor
19 concentration and surface albedo suggests that the errors in input data affect retrieved CER more than COD. Except for
20 some narrow domains that fall within $COD < 15$, the retrieval errors are small for both COD and CER. The retrieved
21 cloud properties reproduce the broadband radiances observed by a narrow FOV radiometer more precisely than broadband
22 irradiances observed by a wide FOV pyranometer, justifying the quality of the retrieved product (at least COD) and
23 indicating the important effect of the instrument FOV in cloud remote sensing. Furthermore, CODs (CERs) from sky
24 radiometer and satellite observations show good (poor) agreement.

25 26 1 Introduction

27 Clouds play an important role in driving the climate system and hydrological cycle (Rosenfeld et al., 2014). The accurate
28 representation of clouds in the global climate model remains one of the largest uncertainties (Forster et al., 2007). Clouds
29 are observed from space with various sensors onboard satellites, and the observations are vital in understanding more
30 about cloud characteristics and their roles in the climate system and hydrological cycle. The quality assurance of cloud
31 properties from satellite observations is an important task in cloud remote sensing, although it is challenging, primarily
32 due to the lack of standard data representing different atmospheric conditions. Compared with the routine observation of
33 aerosols through surface networks, such as AERONET (<https://aeronet.gsfc.nasa.gov/>) and SKYNET

34 (<http://atmos3.cr.chiba-u.jp/skyonet/>), observation of clouds from the surface is performed at a limited number of stations
35 and most of the observation data are not easily accessible. As the recent instruments belonging to AERONET and
36 SKYNET can be used for cloud remote sensing along with aerosol remote sensing, it is important to develop innovative
37 techniques to retrieve cloud properties by using data observed by those instruments. This can help the satellite remote
38 sensing community to validate cloud products and help the whole cloud research community to study clouds in more
39 detail by using high-resolution surface data.

40 Clouds have been studied from the surface by using zenith radiances observed by radiometers belonging to
41 AERONET (e.g., Chiu et al., 2010, 2012) and SKYNET (e.g., Kikuchi et al., 2006). In accordance with the literature, the
42 AERONET and SKYNET radiometers are referred to as sun photometers and sky radiometers, respectively. Similar to
43 space-based cloud remote sensing using reflected signals (e.g., Nakajima and King, 1990), studies using sun photometer
44 and sky radiometer data use a look-up-table (LUT). The fundamental idea is to compare the observed signals with LUT
45 data corresponding to prior known cloud optical depth (COD) and cloud particle effective radius (CER) while finding a
46 plausible solution for the COD and CER combination. This signal can be zenith radiance or transmittance. Chiu et al.
47 (2010) retrieved COD from a LUT of zenith radiances of water non-absorbing wavelengths constructed by assuming a
48 fixed CER, and Chiu et al. (2012) and Kikuchi et al. (2006) used a LUT of transmittances of water non-absorbing and
49 absorbing wavelengths to infer COD and CER simultaneously. The reflected signals for water non-absorbing and
50 absorbing wavelengths can have nearly one-to-one relationships with COD and CER, respectively. On the other hand,
51 transmitted signals do not behave in this manner, making the retrieval process difficult for a LUT approach using
52 transmitted signals. In addition, unlike reflected signals, transmitted signals are weakly sensitive to changes in CER. This
53 makes retrieval using transmitted signals more complex. Furthermore, the shape of the LUT can change depending on
54 the solar position, making the retrieval process even more cumbersome if LUTs developed for a limited number of specific
55 solar positions are used. To overcome these difficulties, some innovative techniques have been proposed. For example,
56 McBride et al. (2011) developed a spectral method by using the slope of the transmittances of 13 wavelengths between
57 1565 and 1634 nm and the transmittance at the visible wavelength of 515 nm to retrieve COD and CER simultaneously.
58 LeBlanc et al. (2015) derived 15 parameters to quantify spectral variations in shortwave transmittances due to absorption
59 and scattering of liquid water and ice clouds, manifested by shifts in spectral slopes, curvatures, maxima, and minima, to
60 discriminate cloud phase and retrieve COD and CER. However, these techniques were developed for radiometers with
61 high spectral resolution and are less suitable for sun photometers and sky radiometers because they have a limited number
62 of channels.

63 Here, we develop a retrieval algorithm based on an optimal estimation method, namely, a maximum a posteriori
64 method (Rodgers, 2000). We use three carefully selected wavelengths to retrieve COD and CER simultaneously. An on-
65 site calibration method is proposed to address the filter degradation problem while analyzing long-term observation data.
66 Although the algorithm is developed using sky radiometer data, it is equally applicable for sun photometer data. The
67 paper begins with a brief description of the sky radiometer in Section 2. The methodology, retrieval error, and quality

68 assessment of retrieved products are discussed in Sections 3–5, respectively. Finally, the conclusion is presented in
69 Section 6.

70

71 **2 Sky radiometer**

72 The sky radiometer (POM-02, PREDE Co. Ltd., Japan) can make observations of direct intensity, angular sky radiance
73 (both almucantar and principle plane scans), and zenith sky radiance at 11 wavelengths at specified time intervals. The
74 field of view (FOV) is 1°. The most commonly used wavelengths by SKYNET are 0.315, 0.34, 0.38, 0.4, 0.5, 0.675, 0.87,
75 0.94, 1.02, 1.627, and 2.2 μm . The direct and angular sky radiances at wavelengths of 0.34, 0.38, 0.4, 0.5, 0.675, 0.87,
76 and 1.02 μm , at which the absorptions by atmospheric gases and water/ice are negligible, are used for aerosol remote
77 sensing (Nakajima et al., 1996; Hashimoto et al., 2012). The direct intensities observed at wavelengths of 0.315 and 0.94
78 μm are used for remote sensing of ozone (Khatri et al., 2014) and water vapor (e.g., Campanelli et al., 2014), respectively.
79 The zenith sky radiances have different potential applications. The zenith sky radiances of cloudy skies have been used
80 for cloud remote sensing (e.g., Kikuchi et al., 2006). The calibration constant terms for sky radiance (angular and zenith)
81 and direct intensity are required while deriving physical data from observation signals via retrieval algorithms. One of
82 the largest benefits of the PREDE sky radiometer is that these calibration constants can be obtained from field observation
83 data, as outlined by Nakajima et al. (1996). In brief, an improved Langley (IL) method (Nakajima et al., 1996; Campanelli
84 et al., 2004), which is an alternative to the normal Langley (NL) method, can be used to obtain calibration constants for
85 direct intensities. Similarly, the solar disk scan method, which is an alternative to integrating sphere method, can be used
86 to determine the calibration constant for sky radiances. A more detailed study about sky radiometers and their calibrations
87 can be found in Khatri et al. (2016).

88

89 **3 Methodology**

90 A schematic of the study method is shown in Fig. 1. We use sky radiances (E) observed at three longer wavelengths (0.87,
91 1.02, and 1.627 μm), excluding 2.2 μm , which is not used for two main reasons. First, our statistical analysis suggests
92 that the number of unphysical data (observation data recorded as 0) for 2.2 μm is high; thus, 2.2 μm is excluded to increase
93 the retrieval number. Second, the longest wavelength used by AERONET is 1.64 μm ; so the proposed algorithm could
94 be easily used for sun photometer observed data as well. Wavelengths shorter than 0.87 μm are not used to avoid the
95 effect of aerosols as far as possible. Observed E can be converted to the transmittance (T) by

$$96 \quad T(\lambda) = \frac{\pi E(\lambda)}{\mu_0 \Delta\Omega(\lambda) F_0(\lambda)}, \quad (1)$$

97 where μ_0 is the cosine of the solar zenith angle, $\Delta\Omega$ is the calibration constant for sky radiance, which is also called the
98 solid view angle by the SKYNET community, F_0 is the calibration constant for direct intensity, and λ is the wavelength.
99 $\Delta\Omega$ for 0.87, 1.02, and 1.627 μm can be determined from the solar disk scan during very clear sky days (Nakajima et al.,
100 1996). Although the current IL method can be used to determine temporal F_0 for the first two wavelengths (0.87 and 1.02
101 μm), it is less suitable for water absorbing wavelengths, such as 1.627 μm . For 1.627 μm , F_0 derived from the NL method

102 can be used, but NL is less practical to implement routinely in short time intervals (e.g., each month) to derive temporal
 103 F_0 . We prefer to use temporal F_0 for all wavelengths to include filter degradation with time (e.g., Khatri et al., 2014). To
 104 derive temporal F_0 at 1.627 μm , we use an alternative IL method, as proposed by Khatri et al. (2014). In brief, aerosol
 105 data (refractive index and volume size distribution) and direct intensity observed at 1.627 μm ($F_{1.627}$) are used. Aerosol
 106 optical thickness (τ_{aer}) depends primarily on aerosol size distribution, and the refractive index makes a small contribution
 107 to τ_{aer} (King, 1978; Khatri and Ishizaka, 2007). Thus, the refractive index at 1.02 μm , which is the highest wavelength for
 108 routine aerosol retrieval, is assumed to be the same as for 1.627 μm while calculating τ_{aer} at 1.627 μm from the volume
 109 size distribution using a Mie calculation. The optical air mass (m) and sun-earth distance (R) are calculated from the
 110 latitude and longitude of the observation site and time. Similarly, the Rayleigh scattering optical depth at 1.627 μm
 111 ($\tau_{\text{Ray},1.627}$), though small in magnitude, is calculated from the atmospheric pressure of the observation site. Finally, the
 112 Beer–Lambert law, $\ln(F_{1.627}R^2) = \ln F_{0,1.627} - (\tau_{\text{aer}} + \tau_{\text{Rayleigh}})m$ is used to determine $\ln F_{0,1.627}$, which is the natural logarithm
 113 of the calibration constant of the direct intensity at 1.627 μm . This is calculated using data for all clear sky periods of
 114 each month to correlate $\ln(F_{1.627}R^2)$ with $(\tau_{\text{aer}} + \tau_{\text{Rayleigh}})m$. The outlier that decreases the correlation most is detected and
 115 removed in each iteration until the condition of the correlation coefficient ($r \geq 0.997$) is satisfied. To understand the
 116 quality of the $\ln F_{0,1.627}$ values calculated with this method, we compare them with data from an independent standard
 117 method. In the standard method, a calibration constant is derived by performing collocated observations with field and
 118 master instruments. Figure 2 compares $\ln F_{0,1.627}$ for three different sky radiometers at the observation sites of Hedo-
 119 misaki (26.87°N, 128.25°E), Fukue-jima (32.75°N, 128.68°E), and Sendai (38.26°N, 140.84°E). There is good agreement
 120 between our method and the standard method for all three sky radiometers. The relative difference (percentage), defined
 121 as the difference between our method and the standard method normalized by the value of the standard method and then
 122 multiplied by 100, is also shown and is less than 0.05% for all sky radiometers. This confirms the validity of our proposed
 123 method, which is inexpensive and easy. Thus, the proposed method can be used to determine temporal variation of
 124 $\ln F_{0,1.627}$, which is useful for analyzing long-term observation data by mitigating the filter degradation problem. By using
 125 the volume size distribution and refractive indices of the wavelengths, the proposed method can be used for 0.87 and 1.02
 126 μm as well. There is negligible difference in the values obtained by the IL method and this method for the first two
 127 wavelengths. This study uses the values obtained from the proposed method for all wavelengths to avoid the difficulty of
 128 reading $\ln F_0$ from different files.

129 Along with the T values of three wavelengths obtained from Eq. (1), we use precipitable water content (PWC) and
 130 spectral surface albedo data, which are obtained from radiosonde observations
 131 (<http://weather.uwyo.edu/upperair/sounding.html>) and MODIS observations (product name: MCD43A4), respectively.
 132 Finally, COD and CER are retrieved simultaneously by minimizing the cost function (J)

$$133 J = (\mathbf{x} - \mathbf{x}_a)^T \mathbf{S}_a^{-1} (\mathbf{x} - \mathbf{x}_a) + [\mathbf{y} - \mathbf{F}(\mathbf{x}, \mathbf{b})]^T \mathbf{S}_y^{-1} (\mathbf{y} - \mathbf{F}(\mathbf{x}, \mathbf{b})), \quad (2)$$

134 where \mathbf{x} is a state vector, \mathbf{x}_a is an a priori vector, \mathbf{S}_a and \mathbf{S}_y are error covariance matrices for the a priori and measurement,
 135 respectively, \mathbf{y} is the measurement vector, \mathbf{F} is the forward model, and \mathbf{b} is the model parameter vector (ancillary data).
 136 The terms \mathbf{x} , \mathbf{y} , and \mathbf{b} are defined as

$$137 \quad \mathbf{x} = \begin{pmatrix} \ln \tau \\ \ln r_e \end{pmatrix}, \quad \mathbf{y} = \begin{pmatrix} \ln T_{1.627} \\ \ln T_{1.02} \\ \ln T_{0.87} \end{pmatrix}, \quad \text{and} \quad \mathbf{b} = \begin{pmatrix} W \\ A_{1.627} \\ A_{1.02} \\ A_{0.87} \end{pmatrix},$$

138 where τ and r_e are COD and CER, respectively, W and A_λ are the PWC and surface albedo at wavelength λ , respectively.
 139 Both \mathbf{S}_a and \mathbf{S}_y are assumed to be diagonal matrices. \mathbf{x}_a and the diagonal elements of \mathbf{S}_a are determined from 1-year data
 140 for water cloud properties observed over Japanese SKYNET sites by the Advanced Himawari Imager (AHI) sensor
 141 onboard Himawari-8, a Japanese geostationary satellite. The diagonal terms for \mathbf{S}_y are determined based on simulation of
 142 perturbations in $T(\lambda)$ generated from 300 random gaussian noises of error sources, as discussed in Section 4. The Santa
 143 Barbara DISORT Atmospheric Radiative Transfer model (Ricchiazzi et al., 1998) is used for forward modeling, and the
 144 Levenberg–Marquardt method is used to minimize the cost function. The total number of iterations is set as 50. If the
 145 solution does not converge within 50 iterations, the analysis is discarded. As highlighted in Sections 1 and 4, transmittance
 146 signals may not always be characterized by unique COD or CER values. Consequently, the initial values of COD and
 147 CER used for iteration can be important when searching the plausible set of COD and CER values. To address this
 148 important issue, we first approximate the initial COD and CER values to start the iteration. The approximation is done by
 149 searching a set of COD and CER values by comparing observed $T_{1.627}/T_{1.02}$ and $T_{1.02}$ with LUT of corresponding values
 150 modeled for COD values of 1–64 and CER values of 2–32 μm in steps of 1 μm . $T_{1.627}/T_{1.02}$ generally decreases with the
 151 increase of COD; whereas when COD increases, $T_{1.02}$ increases first until reaching the peak value, and then starts to
 152 decrease. Thus, $T_{1.627}/T_{1.02}$ and $T_{1.02}$ can be used simultaneously to determine the range of COD and CER in which the
 153 true values are likely to fall. A set of COD and CER values that generate the smallest root mean square difference between
 154 the observed and modeled values is used for the initial values in the iteration.

155 156 **4 Retrieval error**

157 To understand the performance of the proposed algorithm for different types of input data (transmittance and ancillary
 158 data), retrieval errors are calculated by assuming errors on them. The retrieval errors are calculated for COD and CER
 159 values in the ranges of 1–64 and 2–32 μm , respectively, in steps of 1 μm . The simulations are performed for solar zenith
 160 and azimuth angles of 30° and 0°, respectively, by assuming that the cloud phase is water cloud. We assume 1% error in
 161 $\ln F_0(\lambda)$, which is significantly larger than the maximum error in $\ln F_0(\lambda)$ shown in Fig. 2 and discussed in Section 3. This
 162 large error in $\ln F_0(\lambda)$ is assumed to incorporate errors in $T(\lambda)$ generated from other possible sources, such as radiance
 163 measurement and $\Delta Q(\lambda)$ estimation. Similarly, we assume a surface albedo of 0.15 for all three wavelengths and PWC of
 164 1.5 cm by assuming errors of ± 0.025 and ± 1.0 cm, respectively. $F_0(\lambda)$ in actual data analysis is the instrument signal
 165 equivalent to the measurement performed at the top of the atmosphere (TOA); however, the incident irradiance at TOA
 166 (unit: $\text{W}/\text{m}^2/\text{nm}$) calculated from the radiative transfer model is used as $F_0(\lambda)$ for error evaluation simulations discussed
 167 in this section. For each set of known COD and CER, 100 random gaussian noises for each error source are added in the
 168 retrieval to simulate 300 sets of COD and CER. The successful retrievals ($J \leq 3$) are used to calculate the mean bias error
 169 (MBE) as

$$170 \quad MBE = \frac{\sum_{i=1}^n (\frac{S_i}{T_i} - 1)}{n}, \quad (3),$$

171 where S_i and T_i are the simulated and true values, respectively. Only the MBE is discussed here because the error map
 172 evaluated in other forms, such as root mean square error (RMSE), contains the same qualitative information. Figure 3
 173 shows the MBE for COD (first column), MBE for CER (second column), and total number of successful retrievals (third
 174 column) for each type of error separately and in combination. Figures 3(a) – 3(c), 3(d) – 3(f), 3(g) – 3(i), and 3(j) – 3(l)
 175 correspond to the errors in transmittance, surface albedo, PWC and all sources, respectively. The 100% unsuccessful
 176 retrieval is shown in black. The retrieval is more uncertain mainly when COD is less than ~ 15 . Regardless of the error
 177 source, the retrieval error is high, especially for small ($CER < \sim 7 \mu m$) and large ($CER > \sim 13 \mu m$) cloud droplets. In
 178 general, the error domains of CER are expanded by overlapping the error domains of COD. This suggests that the error
 179 in input data affects CER retrieval more than COD retrieval. Among the three error sources, the error in transmittance
 180 can dominate the effect of the remaining two error sources. The successful retrieval number corresponding to each error
 181 source suggests that in the domains $\sim 8 < COD < \sim 16$ with $CER > \sim 13 \mu m$ and $CER < \sim 7 \mu m$, the algorithm has difficulty
 182 fitting the measured transmittances with modeled values. These domains have high retrieval errors (first and second
 183 columns). The high errors in COD and CER are extended further for $COD < \sim 8$ despite the sufficient number of successful
 184 retrievals. The contour lines for $T(\lambda)$ in Figs. 4(a), 4(b), and 4(c) for wavelengths of 0.87, 1.02 and 1.627 μm , respectively
 185 can help to understand these domains. The $T(\lambda)$ values in Figs. 4(a) – 4(c) correspond to no error in the input data.

186 First talking about unsuccessful retrievals noted for $\sim 8 < COD < \sim 16$ and $CER > \sim 13 \mu m$ domain, the $T(\lambda)$ values
 187 hardly change as CER increases above $\sim 13 \mu m$ (Figs. 4(a)–4(c)). As a result, the CER retrieval above $\sim 13 \mu m$ is uncertain
 188 and the retrieved CER is generally underestimated. $T(\lambda)$ contour lines falling within $\sim 8 < COD < \sim 16$ appear again for
 189 $COD < \sim 2$. Therefore, to search for the best set of COD and CER by trying to fit the inputted $T(\lambda)$ values with the modeled
 190 values, the algorithm can mistakenly search for a plausible solution in this small COD domain. If this happens, the
 191 retrieval may not be confined within $J \leq 3$. The algorithm is likely to compensate for such underestimated CERs by
 192 overestimating CODs (Figs. 3(a) and 3(b), and 3(j) and 3(k)).

193 Similarly, for failed retrievals for $CER < \sim 7 \mu m$, a non-uniform change in $T(1.627 \mu m)$ associated with the change
 194 in CER (Fig. 4(c)), can be an important factor. The non-uniform response of CER to the change of $T(1.627 \mu m)$ can
 195 mislead the algorithm while searching for the best set of COD and CER and may force the algorithm to shift wrongly to
 196 the $COD < \sim 2$ domain to search for a plausible solution. Both CER and COD may be overestimated for $CER > \sim 7 \mu m$.
 197 Despite a sufficient number of successful retrievals, there are high errors in the retrieved values for $COD < \sim 8$. Similar
 198 to the error domains discussed above, the retrieval errors are mainly confined to large and small values of CER. The peak
 199 values of $T(\lambda)$ generally fall within $\sim 3 \leq COD \leq \sim 6$. Both the forward scattering and absorption can increase with the
 200 increase of COD along with the increase in multiple scattering; the increase in $T(\lambda)$ before the peak value is due to the
 201 dominance of forward scattering over absorption, and vice versa for the decrease in $T(\lambda)$ after the peak value. In other
 202 words, the competition between forward scattering and absorption is maximum to increase or decrease $T(\lambda)$ within this
 203 COD range. CER is as important as COD in the increase or decrease of $T(\lambda)$, and the algorithm must consider changes in

204 COD and CER while searching for a plausible set of COD and CER. Thus, there is a high possibility for the ambiguous
205 solution of COD and CER within this COD range. Therefore, even a small degree of error in input data can change both
206 COD and CER considerably from their true values. Though weak, this phenomenon can be still active in the vicinity of
207 this COD range to bring error in retrieved values even for $COD < \sim 3$. The weak CER response towards $T(\lambda)$ for large
208 CERs plays an important role in introducing errors in retrieved values for large CERs. A very complicated distribution of
209 $T(1.627 \mu m)$ for $CER < \sim 7 \mu m$, as discussed above, can be an important factor for errors noted for relatively small CERs.
210 Further, the appearance of same $T(\lambda)$ values for larger CODs, as discussed above, can be the next important factor for
211 errors noted within $COD < \sim 2$.

212 Overall, the retrieval error in COD is smaller than that in CER, suggesting that the transmittance-based cloud remote
213 sensing is better for COD retrieval than for CER retrieval. Except those error domains, the magnitudes of the retrieval
214 errors are small. For example, for $COD > 15$ and all types of errors, the 5th, 50th, and 95th percentile values of MBE for
215 retrieved COD are -2.0%, -0.6% and 0.82%, respectively, and for retrieved CER they are -4.1%, -0.51% and 7.2%,
216 respectively. For reference, the maximum (minimum) retrieval errors for $COD \geq 20$ and $CER = 10 \mu m$ for a spectral
217 method proposed by McBride et al. (2011) are $\sim 7\%$ ($\sim 2\%$) and $\sim 52\%$ ($\sim 14\%$) for COD and CER, respectively. In Section
218 5, we examine the quality of the retrieved cloud properties based on comparison with standard data obtained from
219 independent sources.

220

221 **5 Comparison with data from independent sources**

222 **5.1 Solar radiation data**

223 The broad-band radiance and irradiance of the shortwave spectral range ($0.3 - 2.8 \mu m$) observed using a narrow-angle
224 radiometer (EKO Instruments Co., Ltd., Japan; FOV: 5°) and a pyranometer (Kipp and Zonen, Netherlands; FOV: 180°),
225 respectively, at Chiba ($35.62^\circ N$, $140.10^\circ E$) every 20 s from December 2015 to December 2016 are used to evaluate the
226 cloud properties observed by the sky radiometer. The narrow-angle radiometer observes the downwelling irradiance
227 signals as voltage in a narrow FOV. The instrument was calibrated by the manufacturer in the laboratory, and the observed
228 signals are converted into radiance (unit: $W/m^2/sr$) by using the company provided calibration constant value. Because
229 the narrow-angle radiometer faces upward, thus obtained radiance is from the zenith. The cloud properties from the sky
230 radiometer are combined with the surface albedo observed by MODIS and the PWC observed by radiosonde to calculate
231 the corresponding observations. A comparison is performed for an average of 5 min observation of solar radiation that
232 centers the sky radiometer observation time. Figures 5(a) and 5(b) compare the broad-band radiance and irradiance,
233 respectively. For reference, a comparison is also performed for modeled values using cloud properties from AHI instead
234 of the sky radiometer for broad-band radiance and irradiance (Figs. 5(c) and 5(d)).

235 For cloud properties from the sky radiometer, there is a strong (weak) correlation between modeled and observed
236 values for broad-band radiance (irradiance). In contrast, for AHI cloud properties, the correlation between the modeled
237 and observed values for broad-band radiance (irradiance) is weak (strong). Compared with data from the pyranometer,
238 the observed data from the narrow-angle radiometer best describes the quality of the sky radiometer cloud properties

239 because of the narrow FOV. The good agreement in Fig. 5(a) with a correlation coefficient (r) of up to 0.93 suggests that
240 sky radiometer cloud properties (at least COD) are qualitative enough. Because the contribution of COD is greater than
241 that of CER to broad-band solar radiation (Khatri et al., 2018), Fig. 5(a) alone cannot explain the quality of the retrieved
242 CER. The poor agreement for irradiance comparison in Fig. 5(b) can be explained by the large difference in FOV of the
243 sky radiometer and pyranometer; the surface observed solar radiation varies drastically depending on the instrument FOV.
244 For example, in the scatter plot for broad-band irradiance observed by pyranometer and radiance observed by a narrow-
245 angle radiometer at Chiba during January–March 2016, the correlation is poor (Fig. 6). An important factor in decreasing
246 the correlation between these measurements is the cloud horizontal inhomogeneity, which can explain the poor agreement
247 in Fig. 5(b) plausibly, despite the accurate retrieval from the sky radiometer (Fig. 5(a)). In contrast, the AHI cloud
248 properties are average or representative values of specific coverage, for instance, a pixel (e.g., 1×1 km). As a result, the
249 irradiances modeled with the AHI cloud properties are closer to the observed irradiance than those modeled with the sky
250 radiometer cloud properties. This is because the cloud observed by the sky radiometer can be a small portion of a pixel
251 containing horizontally inhomogeneous clouds.

252

253 **5.2 Satellite cloud products**

254 As part of validating the water cloud products of MODIS and AHI using surface radiation data, Khatri et al. (2018)
255 compared water cloud properties retrieved from sky radiometers at the SKYNET observation sites of Chiba, Hedo-misaki,
256 and Fukue-jima with those of MODIS and AHI observations for October 2016 to December 2017. They used surface
257 irradiance data, and the validation results using sky radiometer and surface irradiance data were qualitatively similar. A
258 good (poor) agreement was shown for COD (CER) between sky radiometer and satellite products in Khatri et al. (2018).
259 They compared sky radiometer results with results of collocated satellite pixels by selecting samples with a time
260 difference of less than 1.25 min, which is half the temporal resolution of the AHI observations over Japan. The distance
261 between the pixel center and the observation site was less than 1 km, and they performed parallax correction for satellite
262 products.

263 In Section 5.1, we identified the inhomogeneous clouds and broken clouds in the satellite pixels as major obstacles
264 in assessing the quality of satellite products using the sky radiometer results and vice versa. Here, we examine the quality
265 of sky radiometer products by using satellite products. We prepare samples for comparison by addressing the cloud
266 inhomogeneity problem in a logical way with the available information. If the surface irradiance calculated from the sky
267 radiometer cloud properties agrees well with that observed at the surface, the effective COD of the actual inhomogeneous
268 clouds may be represented by a sky radiometer COD. The effective COD refers to the COD of the assumed plane-parallel
269 homogenous cloud layers, which can produce irradiance equivalent to that produced by actual inhomogeneous clouds,
270 that is, the measured irradiance. The satellite cloud properties retrieved from reflected signals assume clouds are plane-
271 parallel homogenous layers. The sky radiometer cloud properties that generate surface irradiances equivalent to observed
272 values by differing by not more than 1% are compared with the satellite cloud properties. Figures 7(a) and 7(b) compare
273 the sky radiometer CODs with MODIS and AHI values, respectively, for the same sites and period as Khatri et al. (2018).

274 The COD agreement is good. The results are qualitatively same for both MODIS and AHI, with r values of ~ 0.6 and ~ 0.7
275 and RMSE values of ~ 13 and ~ 10 for MODIS and AHI, respectively. Despite several differences between the sky
276 radiometer and satellite products from observation and retrieval, their good agreement indicates that they have a similar
277 response towards thin and thick clouds. Similarly, Figures 8(a) and 8(b) compare the sky radiometer CERs with MODIS
278 and AHI values, respectively. The water absorbing wavelengths corresponding to MODIS and AHI are 2.1 and $3.79 \mu\text{m}$,
279 respectively. The CERs between the sky radiometer and satellite sensors are poorly correlated, with r less than 0.12 and
280 RMSE of $\sim 7 \mu\text{m}$ for both satellite sensors. This poor correlation may be mainly due to the high sensitivity toward cloud
281 top layers of the satellite sensors using reflected signals (Platnick, 2000), whereas sky radiometers are sensitive to all the
282 cloud layers.

283 Although the qualitative information reported by Khatri et al. (2018) and the comparisons in Figures 7 and 8 of this
284 study are similar, there are differences in Figures 7 and 8 with the comparison plots shown in Khatri et al. (2018). The
285 application of data screening criteria in this study generally screened out data with large differences between the sky
286 radiometer and satellite sensors. These large differences in the previous comparison probably arose from the different
287 FOVs of the satellite sensor and sky radiometer, while observing inhomogeneous clouds. Thus, the comparison results
288 presented in this study by addressing the cloud inhomogeneity problem more logically should give more accurate and
289 refined information than those presented in Khatri et al. (2018).

290

291 **6 Conclusions**

292 To make cloud observation from the surface more common and convenient, we developed an algorithm to retrieve cloud
293 properties (COD and CER) from spectral zenith radiances measured by sky radiometer. By considering a priori
294 information of the state vector and errors related to observed transmittance and using ancillary data (PWC and surface
295 albedo), an optimal estimation approach was proposed by fitting the observed transmittances at wavelengths of 0.87 , 1.02 ,
296 and $1.627 \mu\text{m}$ with modeled values. To ease data analysis of long-term observations further by overcoming the filter
297 degradation problem, an on-site method of calibrating for direct intensity was proposed by using aerosol data for clear
298 sky days. The calibration constants derived from the proposed method agree well with values determined by collocating
299 the field instruments with the master instrument. The retrieval error analyses performed by considering known ranges of
300 errors in the observed transmittances and ancillary data suggested that the algorithm performed well, except for in narrow
301 bands of small COD and CER values. In general, the errors in input information affected CER retrieval more strongly
302 than COD retrieval, and the retrieved CER had large errors when clouds were optically thin ($\text{COD} < \sim 15$) and cloud
303 droplets were small ($\text{CER} < \sim 7 \mu\text{m}$) or large ($\text{CER} > \sim 13 \mu\text{m}$). As part of the quality assessment, cloud properties retrieved
304 from the proposed algorithm were compared indirectly with surface observed radiance and irradiance data and directly
305 with observed cloud properties from MODIS and AHI. The retrieved cloud properties produced broadband shortwave
306 radiances similar to those observed by a narrow-angle radiometer, confirming the good quality of the retrieved products
307 (at least COD) from the sky radiometer. However, the agreement was poor when broadband shortwave irradiances
308 observed by a pyranometer with a wide FOV were compared with the modeled values. This discrepancy was probably

309 caused by the large difference in FOVs between the sky radiometer and pyranometer, suggesting that the instrument's
310 FOV has a large effect on cloud remote sensing. COD agreed well between the sky radiometer and satellite sensors;
311 however, the agreement was poor for CER.

312
313 *Code/Data Availability:* Data and retrieval code are available from the corresponding author upon request.

314
315 *Author Contribution:* PK, HI, and TH developed study framework and code. HI, TT, AY, and AD generated data. HL
316 and QK helped in advancing study framework and manuscript writing. All co-authors read the manuscript and provided
317 suggestions and comments.

318
319 *Competing interests:* The authors declare that they have no conflict of interest.

320
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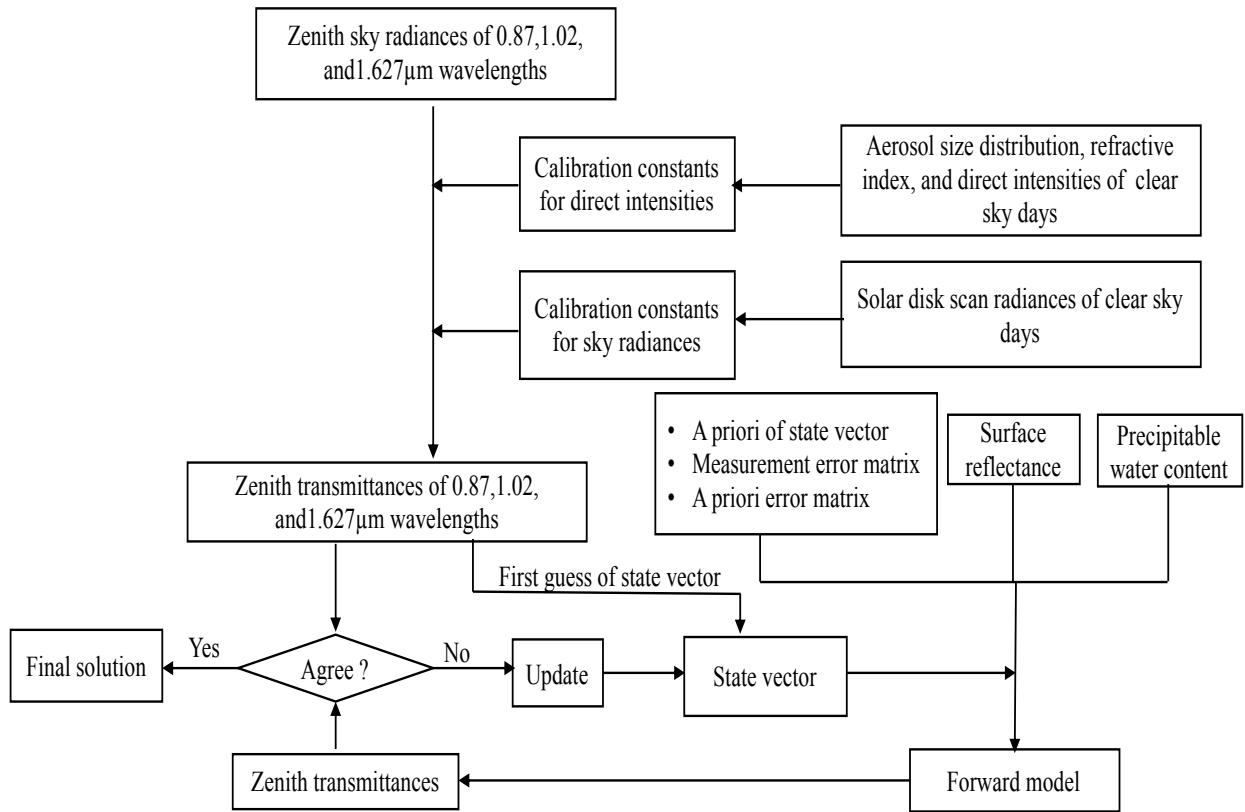
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414 **Figures**

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418 **Figure 1: Schematic of the study method.**

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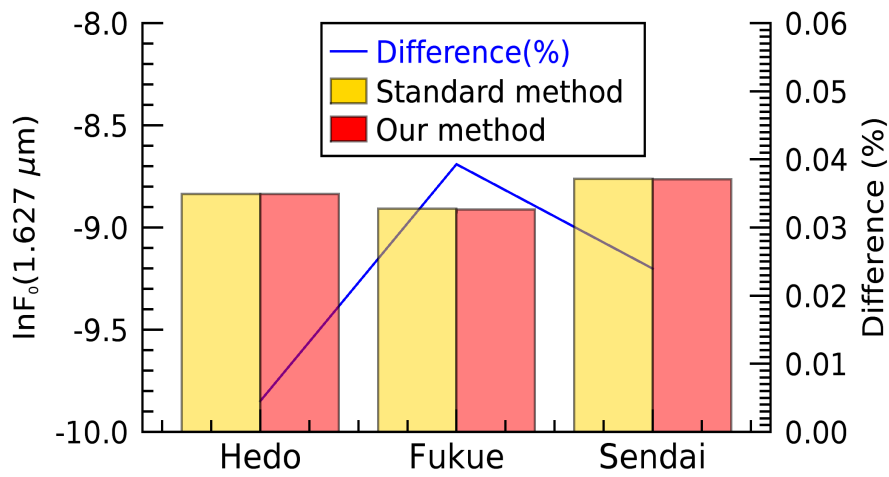
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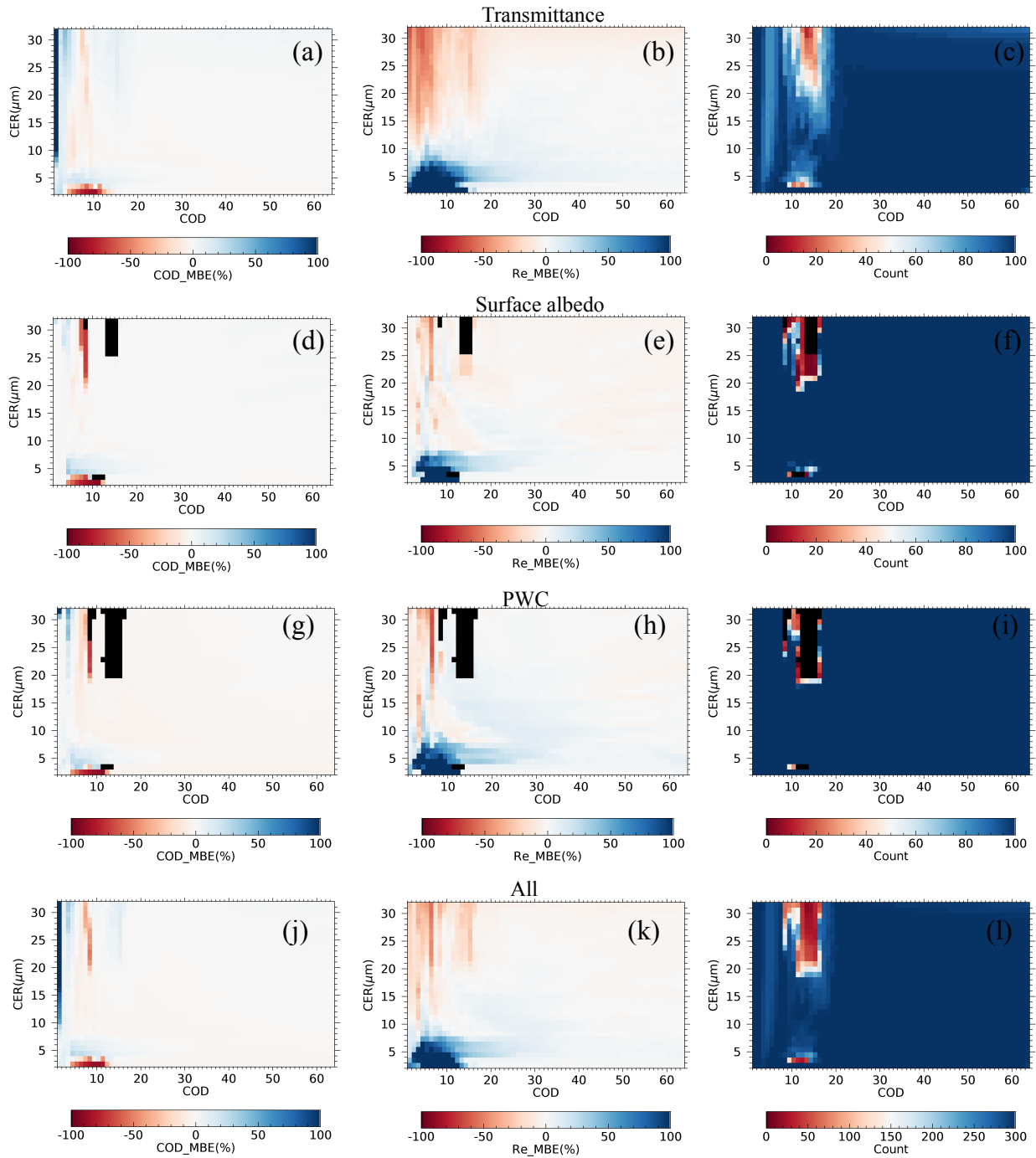
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429 **Figure 2: Comparison of the direct intensity calibration constant ($\ln F_0$) values at the water absorbing wavelength**
 430 **of 1.627 μm for the standard method (calibration using the master instrument) and our on-site method for sky**
 431 **radiometers at Hedo-misaki (26.87°N, 128.25°E), Fukue-jima (32.75°N, 128.68°E), and Sendai (38.26°N, 140.84°E).**
 432 **The difference (%) is also shown, which is the difference (percentage) between the proposed method and the**
 433 **standard method normalized by the value of the standard method and multiplied by 100.**

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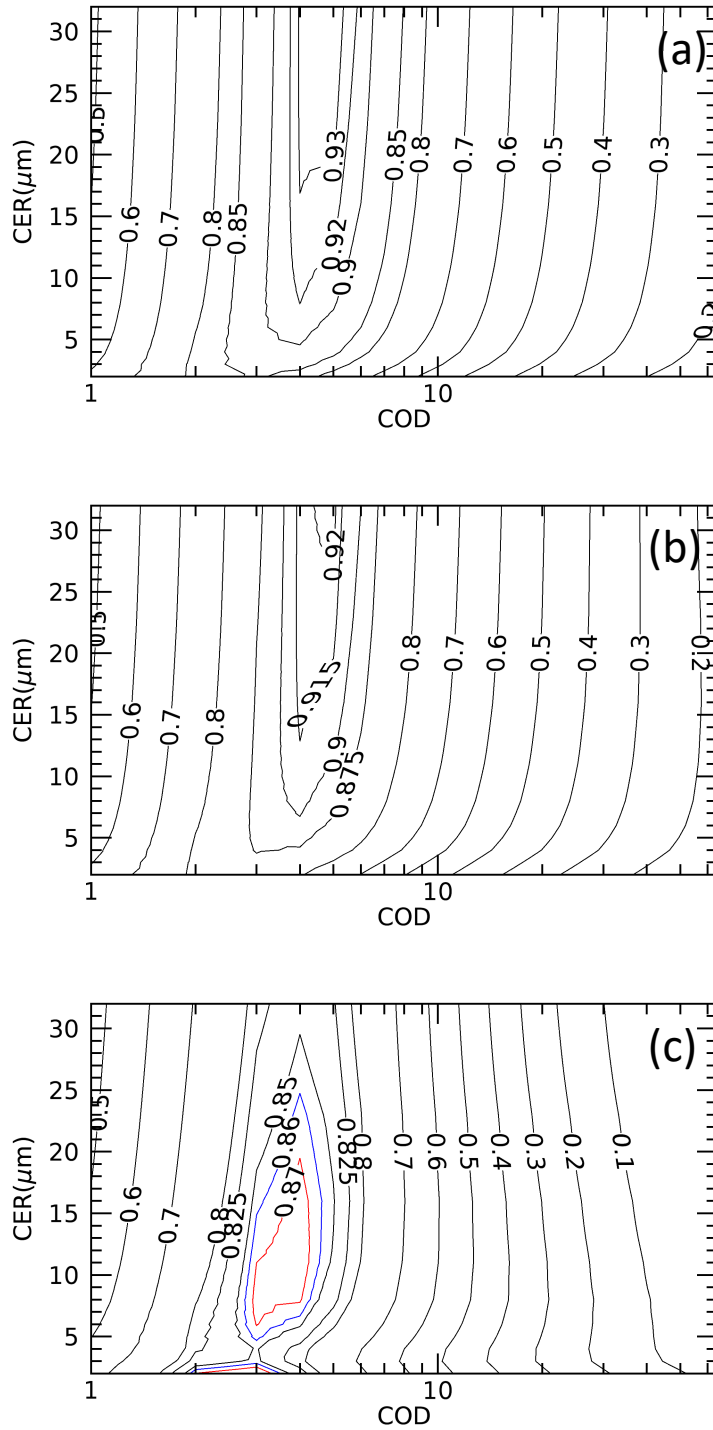
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Figure 3: Mean bias error (MBE) values for retrieved (a) cloud optical depth (COD) and (b) cloud particle effective radius (CER), and (c) total number of successful retrievals for assumed error in transmittance; (d)–(f): same as upper panel but for assumed error in surface albedo; (g)–(i): same as upper panel but for assumed error in precipitable water content; (j)–(l): same as upper panel but for all error sources. The 100% unsuccessful retrieval is shown in black.

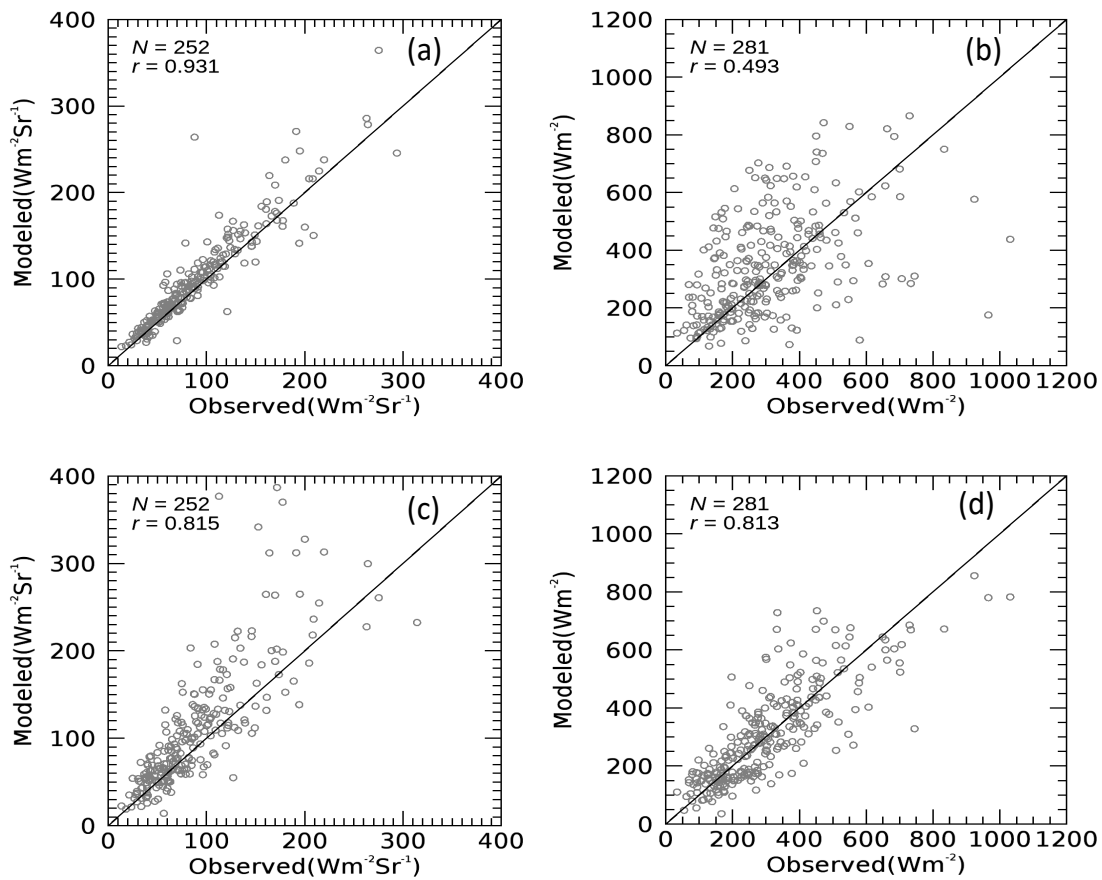


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443 **Figure 4: Contour plots of transmittances at wavelengths of (a) 0.87, (b) 1.02, and (c) 1.627 μm for solar zenith and**
 444 **azimuth angles of 30° and 0°, respectively. The transmittance values are given within the contour lines. Different**
 445 **colors are used for 1.627 μm to make it easy to distinguish. COD, cloud optical depth; CER, cloud particle effective**
 446 **radius.**

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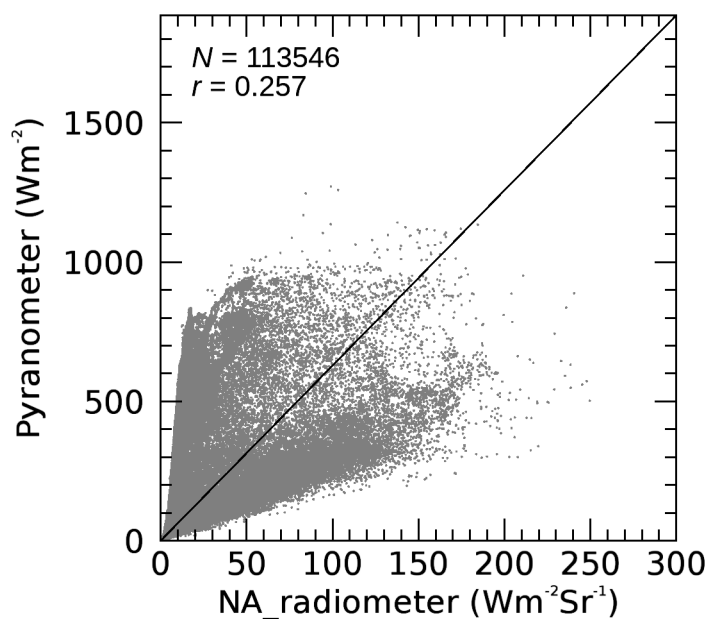
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450 **Figure 5: Comparison of modeled and observed broad-band (a) radiances and (b) irradiances for modeled values**
 451 **using sky radiometer cloud proprieties for the observation site at Chiba (35.62°N, 140.10°E) for 2016. (c) and (d)**
 452 **Comparison results for broad-band radiances (c) and (d) irradiance for modeled cloud properties corresponding**
 453 **to the Advanced Himawari Imager.**

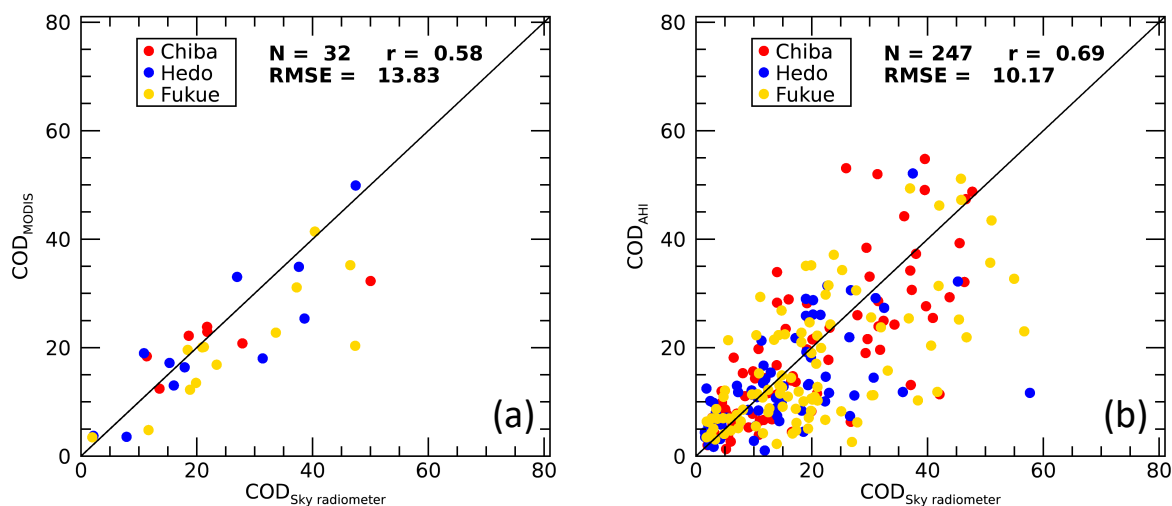
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456 **Figure 6: Scatterplot of broad-band radiances and irradiances observed with a narrow-angle radiometer and a**
 457 **wide-angle pyranometer at Chiba (35.62°N, 140.10°E) during January–March 2016. The solid line represents**
 458 **$y = 2\pi x$.**

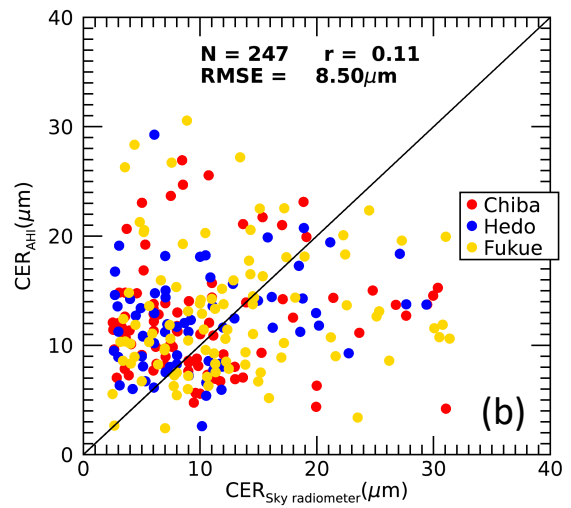
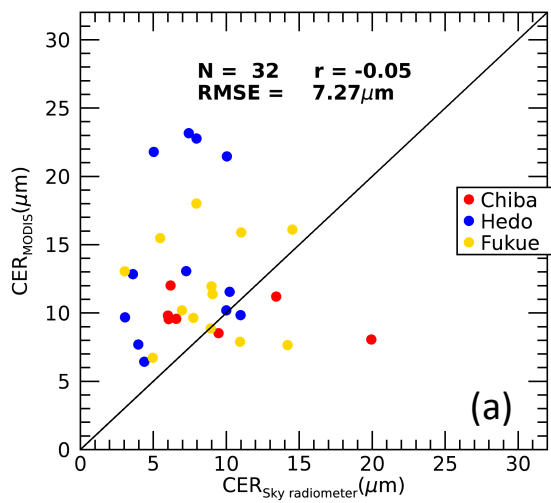
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461 **Figure 7: Comparison of sky radiometer cloud optical depths (CODs) with (a) MODIS and (b) Advanced**
 462 **Himawari Imager CODs for observation sites at Chiba (35.62°N, 140.10°E), Hedo-misaki (26.87°N, 128.25°E), and**
 463 **Fukue-jima (32.75°N, 128.68°E) from October 2015 to December 2016.**

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465

466 **Figure 8: Same as Figure 7, but for comparison of cloud particle effective radii (CERs).**