Intercomparison of Cloud Amount Datasets in the Kuroshio Region over the East China Sea

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Abstract

The cloud variability and regime transition from stratocumulus to cumulus across the sea surface temperature front in the Kuroshio region over the East China Sea are important regional climate features and may affect the Earth’s energy balance. However, because of large uncertainties among available cloud products, it is unclear which cloud datasets are more reliable for use in studying the regional cloud features and in validating cloud simulations in the region by climate models. In this study, the monthly low cloud amount (LCA) and total cloud amount (TCA) datasets in the region from Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO), Moderate-resolution Imaging Spectroradiometer (MODIS), and International Comprehensive Ocean–Atmosphere Data Set (ICOADS) are validated against the combined product of CloudSat + CALIPSO (CC) in terms of consistency and discrepancy in the climatologically mean, seasonal cycle, and interannual variation. The results show that LCA and TCA derived from MODIS and CALIPSO present relatively high consistency with CC data in the climatological annual mean and show similar behaviors in seasonal cycle. The consistency in LCA between the three datasets and the CC is generally good in cold seasons (winter, spring, and fall) but poor in summer. MODIS shows the best agreement with CC in fall, with a correlation coefficient of 0.77 at a confidence level over 99%. CALIPSO and MODIS can provide a competitive description of TCA in all seasons, and ICOADS is good in terms of the climatological seasonal mean of TCA in winter only. Moreover, the interannual
variation of LCA and TCA from all datasets is highly correlated with that from CC in both winter and spring with the Matching Score ranging between 2/3 and 1. Further analysis with long-term data suggests that both LCA and TCA from ICOADS and MODIS can be good references for studies of cloud interannual variability in the region.

Keywords  low cloud amount; total cloud amount; ICOADS; satellite observation; climatology; interannual variation

1. Introduction

Clouds play a vital role in the radiation budget of the Earth’s climate system. Low clouds act to cool the climate system by reflecting solar radiation back to space, thus reducing incoming solar radiation at the surface (Ramanathan et al. 1989; Klein and Hartmann 1993). They involve many kinds of atmospheric processes, including freshwater, moisture transport, and air–sea heat and moisture exchanges (Wielicki et al. 1995). As such, low clouds are crucial for the estimation of the energy budget and air–sea interactions. They have been identified as a primary source of uncertainties in predicting future climate change (Bony et al. 2015).

The Kuroshio current over the East China Sea transports a large amount of heat from the tropics to the mid-latitudes (Zhang et al. 2012), influencing the regional climate (Hu et al. 2015). The Kuroshio current, as one of the western boundary currents, produces a sharp sea surface temperature (SST) front, which has a significant impact on the atmospheric circulation and clouds (Xie et al. 2002; Minobe et al. 2008; Xu et al. 2011; Li and Zhang 2013). The changes of the cloud optical depth and cloud top height during cloud transition from stratocumulus to cumulus over the SST frontal region are still hard for climate models to simulate (Field et al. 2017) and thus often result in a large bias in climate simulations (Chepfer et al. 2010). Moreover, the change in low clouds in this region not only influences precipitation, radiation budget, and ocean primary productivity but also is a factor important for understanding the underlying processes in the adjustment of the marine-atmospheric boundary layer to the Kuroshio SST front (Xie 2004; Small et al. 2008; Liu et al. 2016).

The importance of low clouds to regional climate leads to a necessary effort to map their properties and comprehend the mechanisms of their variation. Although Hagihara et al. (2010) investigated globally the performances in CA detection among Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO), CloudSat–CALIPSO, and Moderate-resolution Imaging Spectroradiometer (MODIS), few studies have focused on cloud climatology, particularly the interannual variation and secular changes in the Kuroshio region over the East China Sea (ECSK). The primary limitation is the lack of long-term and homogeneous cloud data. Surface marine observations are immensely valuable for climate studies (Norris 1998a, b; Clement et al. 2009) owing to the long-term record for several decades, taking the International Comprehensive Ocean–Atmosphere Data Set [ICOADS (Worley et al. 2005), described below] as an example. However, the observational methods are neither homogeneous nor routinely collected. Therefore, it is imperative that the long-term products be validated against more advanced products in order to examine the reliability of various data sources for the study of their interannual variability.

Satellite cloud products are an important part of data sources in the studies of clouds, although their qualities are dependent on retrieval algorithms and instrument capabilities (Stubenrauch et al. 2013). For instance, the International Satellite Cloud Climatology Project (ISCCP) was initiated in 1983 (Schiffer and Rossow 1983) with relatively long cloud record (Table 1). However, it estimates clouds just by relying on two spectral channels in combination with variability through time, and the latest products with more advanced instruments use over 20 spectral bands, which can provide a higher probability of accurate detection of clouds as evaluated over Europe (Kotarba 2015). One of the advanced satellites is MODIS (Platnick et al. 2003), with 36 visible (VIS), near-infrared (NIR), and infrared (IR) regions of the spectrum from 0.4 to 14.5 μm.

Despite the improvement in measuring cloud amounts, most of the multi-layer cloud information could not be retrieved from passive sensor data, especially in the East Asian monsoon region, where multi-layer clouds are more frequent because of the compli-
cated atmospheric perturbations (e.g., Mei-Yu front and typhoons) and strong SST front forcing (Xie et al. 2002; Liu et al. 2016). Active remote sensors can detect cloud vertical structures comprehensively. In April 2006, CloudSat (Stephens et al. 2002), carrying the Cloud Profiling Radar (CPR, Im et al. 2005), and CALIPSO (Winker et al. 2003), fielding the Cloud–Aerosol Lidar with Orthogonal Polarization (CALIOP, Winker et al. 2007), were launched to join the A-Train constellation. The CPR is a 94 GHz radar, which is able to probe optically thick large particle layers, and CALIOP has the specialty of sensing optically thin layers and tenuous cloud tops (Kay and Gettelman 2009). Therefore, with complementary skills, the combined cloud product with CPR and CALIOP can supply a comprehensive picture of global clouds.

Many studies have demonstrated the credibility of CloudSat/CALIPSO data (hereafter, CC) compared with ISCCP and ground observational data (Sassen and Wang 2008; Naud and Chen 2010; Jiang et al. 2011; Noh et al. 2011; Yan et al. 2016). Unfortunately, the CC data are short in record and only available for the period from 2006 to 2011 because of the battery problem of the CloudSat in 2011. Nevertheless, even though short in record, the CC data can be considered as a baseline to validate other datasets that have long records for the same period (e.g., ISCCP, MODIS, and ICOADS) and can still be used to study the climatological annual mean, seasonal cycle, and even interannual variability.

In this study, we perform an assessment of the most representative cloud datasets, including ICOADS, MODIS, and CALIPSO, based on the CC dataset in the ECSK and attempt to intercompare the dominant modes of variability of cloud amounts derived from ICOADS and MODIS. Data intercomparison and cross validation can help in understanding both the advantages and disadvantages of different datasets in representing cloud amounts in the region. Therefore, the results from this study can be a good reference for the study of clouds in the ECSK region and help further understanding the regional climate variability and the Earth’s energy balance. The rest of the paper is organized as follows. Section 2 briefly introduces four datasets considered in this study. Section 3 presents an intercomparison of the four datasets in presenting low cloud amount (LCA) and total cloud amount (TCA) on the climatological annual mean, seasonal cycle, and interannual variability. Concluding remarks are given in the last section.

2. Data and methodology

2.1 Satellite data

Cloud amount (CA) in satellite data is defined as the ratio between the number of samples that contain clouds and the total number of measured samples (Stubenrauch et al. 2013). Low clouds in satellite data are classified when the cloud top pressure is below 680 hPa, with middle clouds between 680 and 400 hPa and high clouds above 400 hPa.

a. CALIPSO cloud data

CALIOP is a 532/1064 nm depolarization lidar onboard CALIPSO. The combination of these two wavelengths is highly sensitive to both optically thin and low clouds and aerosols (Liu et al. 2009; Notar nicola et al. 2011). CALIOP provides a cloud vertical profile with a vertical resolution of 50 m below 8 km and 60 m above at a wavelength of 532 nm. The horizontal resolution for 532 nm is 333 m (along track) 75 m (cross track) below 8 km and 1 km × 75 m above. In our study, the monthly gridded product, general circulation model-oriented CALIPSO Cloud Product (hereafter referred to as CALIPSO (Chepfer et al. 2010)) with a horizontal resolution of 1° × 1° and vertical resolution of 480 m, is employed in comparison. It diagnoses cloud properties using different scattering ratio (SR) thresholds in each lidar profile, such as cloudy (SR > 5), clear (0.01 < SR < 1.2), fully attenuated (SR < 0.01), or unclassified (1.2 < SR < 5) (Chepfer et al. 2008).

CloudSat and CALIPSO are members of the A-Train constellation. The latter trails the former by approximately 15 s. They provide a global view from 82°S to 82°N with a 16-day repeating cycle. The combination of CloudSat and CALIPSO is introduced as follows.

b. CloudSat + CALIPSO cloud data (hereafter CC)

The CPR, a 94 GHz radar onboard CloudSat, can penetrate deep and large particle clouds, but is insensitive to thin cirrus and small particle layers. The combination of CPR and CALIOP is particularly valuable in studying the vertical structure of clouds and has a potential to give a complete picture of cloud and aerosol (Kay and Gettelman 2009; Luo et al. 2009). In our study, the CA of CC is combined by the 2B-GEOPROF cloud mask and the 2B-GEOPROF-lidar cloud fraction based on the method described by Kay and Gettelman (2009). The CA is set to 100 % when the cloud mask is 20, 30, or 40. Otherwise, CA is equal to the maximum cloud fraction in the vertical
interval (Kay and Gettelman 2009; Luo et al. 2009; Marchand et al. 2009). This method to retrieve CA is similar to the C4 scheme, either CloudSat or CALIPSO, as described in Hagihara et al. (2010). More information can be found on the website (http://www.cgd.ucar.edu/staff/jenkay/cloudsatcalipso/). For spatial consistency, we interpolated the combined data at a horizontal resolution of $2^\circ \times 2^\circ$ and vertical resolution of 480 m into “MODIS-like” grids ($1^\circ \times 1^\circ$).

c. MODIS cloud data

MODIS is an imaging radiometer onboard the Terra and Aqua satellites and measures radiances of the Earth’s land, oceans, and atmosphere at 36 wavelengths with the spectrum from the visible to thermal infrared (0.4 to 14.5 $\mu$m) and spatial resolution from 250 m to 1 km (Li et al. 2003; Pincus et al. 2012; Chan and Comiso 2013). It can be a useful supplement to the ISCCP record (Pincus et al. 2012; Kotarba 2015).

MCD08 cloud mask with global grids with 1.0° $\times$ 1.0° is a combination of MYD08, MOD08, and MODIS Level-3 monthly products from Aqua and Terra (Pincus et al. 2012). The passive remote sensing instruments are easily obscured by upper-level clouds (middle and high clouds) when they detect low clouds. Therefore, it is necessary to adjust MODIS LCA data based on randomly overlapped assumption. The LCA is adjusted by the equation below, after (Rozendaal et al. 1995; Mansbach and Norris 2007; Myers and Norris 2013):

$$L' = \frac{L}{(1 - M - H)},$$

where $L$, $M$, and $H$ are the given low, middle, and high CAs, respectively. $L'$ is the corrected LCA. This assumes that the actual clouds are randomly overlapped.

2.2 Surface data

ICOADS is a surface marine observational dataset collected from ships, buoys, and other platforms. CA refers to the fraction of the sky covered by clouds when observed from a particular location. Observers typically identify low clouds when the cloud base is below 2 km and middle (high) clouds when the base is between 2 and 7 km (between 5 and 13 km) in temperate regions (Houze 1993). Observers visually estimate CA on an octa scale. Its values range from 0 to 9, where 0 corresponds to clear sky and 8 to overcast. The additional value 9 presents no observation because of fog, precipitation, or other insufficient light conditions. The octa scale is converted to fractional CA, assuming that 1 octa is equal to 12.5 % (Rossow et al. 1993; Kotarba 2009). According to Houze (1993), we employed low cloud types including stratus (low-cloud-type codes C_6), stratocumulus (C_L 4 5 8), and cumulus (C_L 1 2 7). Among these low cloud types, low clouds with deep convection were excluded.

All grids with total observations of low/total clouds more than 100 records were adopted in our analyses. In each month, we omitted the records with an observational count less than 15. A relatively high frequency of low clouds occurred in winter and fall, which is similar to the results of Norris (1998b) and indicates that samples over the ECSK can provide a confident support for our analyses. The frequency of occurrence of low clouds (FQ$_{ld}$) was calculated as follows.

$$FQ_{ld} = \frac{N_{ld}}{N_{all}},$$

where $N_{ld}$ is the total count of observations with report of low clouds and $N_{all}$ is the total count of all cloud observations. The averaged LCA (ALCA) was calculated by

$$ALCA = FQ_{ld} \times TALCA,$$

where TALCA is the average value of total reports of LCA in the given period following Norris (1998b).

2.3 Methodology

In order to take full advantage of limited satellite data, we extracted the CA of these datasets with the same period (December 2006 to November 2010, Table 1) and the same grids in the ECSK (123.5°E–133.5°E; 23.5°E–31.5°E, the black rectangle shown in Fig. 1d). We tended to preserve an equal-angle grid ($1^\circ \times 1^\circ$) according to MODIS and CALIPSO datasets and bilinearly interpolated other data onto “MODIS-like” grids. This process can help in reducing some interpolation errors (Kotarba 2015). In our analysis, we defined spring from March to May (MAM), summer from June to August (JJA), fall from September to November (SON), and winter from December to the following February (DJF).

As active sensors, CPR and CALIOP have an inherent advantage in identifying low clouds (Kay and Gettelman 2009; Mace et al. 2009). Therefore, the CALIPSO or CC dataset is treated as a baseline to verify other CA products derived from satellites or models in some previous studies (Okamoto et al. 2008; Hagihara et al. 2010). As a confirmation, a cross correlation of LCA among the four datasets was conducted, with the results given in Table 2. The results indicate that the CC presents a relatively high correlation compared with the other datasets, particularly with the correlation coefficient reaching 0.74 with
MODIS, which is over 99 % confidence level. Similar patterns are present for all four seasons (not shown).

In the following analyses, the correlation coefficient (R, significant at ≥ 95 % confidence level if not noted otherwise), the mean of difference (Bias) between each of the three datasets (CALIPSO, MODIS, and ICOADS, hereafter CMI) and CC, Standard Deviation of Difference (STDD), and Root-Mean-Square Error (RMSE) are calculated (Table 3).

### 3. Results

#### 3.1 Annual mean

Hagihara et al. (2010) investigated globally the differences in CA at low, middle, and high levels among CALIPSO, CloudSat–CALIPSO, and MODIS. The results indicate that the TCAs of these datasets are similar, but the LCA is different because of possible misclassification. LCA and TCA are assessed sepa-
Figures 1a–d show the annual mean LCA computed for the common period December 2006–November 2010 obtained from the four datasets described in Section 2. We can see diverse spatial distributions among the four datasets. The spatial patterns of LCA from MODIS and ICOADS (Figs. 1c, d) are coincident with that from CC (Fig. 1a), all showing a cloud band along the Kuroshio SST front. The cloud band is not evident in CALIPSO, however. The averaged values of LCA in the ECSK from all four datasets are given in Table 3. A significant difference exists among these products, and the averaged values are similar between ICOADS and CC (approximately 45 %). Furthermore, relatively larger LCAs along the west coast of the Korean peninsula appearing in both CALIPSO and MODIS (Figs. 1b, c) are absent in ICOADS (Fig. 1d).

The LCA obtained from MODIS is well correlated with that from CC, with a correlation coefficient of 0.74 exceeding 99 % confidence level (Fig. 2b). Almost 50 % of all MODIS–CC differences are within the range between 0 % and 20 % with a relatively small STDD, indicating a significant systematic bias of 14.40 % (Fig. 2d). The larger LCA from MODIS is related to three possible reasons. First, according to Eq. (1), the MODIS LCA increases when the influence of middle and high clouds is eliminated. Second, the original MODIS cloud top pressure with 5 km resolution overestimates the cloud top pressure and LCA (Holz et al. 2008; Hagihara et al. 2010; Pincus et al. 2012). Third, the higher cloud amounts in MODIS compared to CC could also be due to a coarser resolution (see Table 1). Note that the original MODIS data compared with the CC data are unsurprisingly worse than the corrected MODIS data (not shown).

The relationship between ICOADS and CC is comparable, with a correlation coefficient of 0.5. Figure 2d shows that the peak of frequency distribution of the ICOADS–CC difference only shifts slightly to the right with a bias of 1.95 %. Therefore, the LCA from ICOADS has a potential to provide a good reference in terms of the climatological annual mean. The larger bias and RMSE between CALIPSO and CC (Figs. 2a, d) indicate the disadvantage of CALIPSO in penetrat-

### Table 2. Linear correlation of LCA in all samples

| Sample number (4752) | ICOADS | MODIS | CloudSat + CALIPSO | CALIPSO |
|---------------------|--------|-------|-------------------|--------|
| ICOADS              | 1.00   | 0.449 | 0.495             | 0.304  |
| MODIS               | 0.449  | 1.00  | 0.740             | 0.419  |
| CloudSat + CALIPSO  | 0.495  | 0.740 | 1.000             | 0.487  |
| CALIPSO             | 0.304  | 0.419 | 0.487             | 1.000  |

### Table 3. TCA and LCA statistics for the CMI with respect to CC (unit: %)

| LCA      | CC     | TCA     |
|----------|--------|---------|
|         | Mean   | R   | Mean | Bias | STDD | RMSE |
| annual  | 45.59  | 0.49| 31.41| -14.18 | 21.44| 19.98|
| DJF     | 66.28  | 0.31| 41.39| -13.13 | 22.28| 23.45|
| MAM     | 41.39  | 0.25| 26.24| -9.67  | 19.23| 19.34|
| JJA     | 26.24  | 0.14| 17.56| -11.49 | 13.43| 13.97|
| SON     | 48.45  | 0.37| 26.76| -17.56 | 10.01| 14.50|
|         |        |     |      |       |       |       |
| annual  | 68.66  | 0.55| 68.27| -0.39  | 19.58| 19.59|
| DJF     | 68.28  | 0.51| 69.89| 0.56   | 19.70| 19.96|
| MAM     | 69.89  | 0.55| 71.03| 0.51   | 18.43| 18.86|
| JJA     | 71.03  | 0.61| 71.55| 3.27   | 19.29| 20.26|
| SON     | 65.45  | 0.56| 64.79| -1.68  | 19.34| 19.40|

* Except for correlation coefficient, other quantities are calculated from the difference between each dataset of the CMI and CC. The coefficients (R) without grey shades mean over 95 % confidence level.
b. Total cloud amount (TCA)

Figures 1e–h show the TCA from the four datasets. CALIPSO, MODIS, and ICOADS give similar spatial patterns of TCA, with an evident cloud band and peak value to the northeast of Taiwan Island. The averaged values of TCA over the ECSK in the three datasets are also similar (approximately 68%), but those in MODIS are considerably higher (75.25%; Table 3 and Fig. 2h). In addition, a relatively high correlation between MODIS and CC with a small STDD indicates a systematical bias in MODIS (Figs. 2f, h). In contrast, the relationship between ICOADS and CC tends to be random (Fig. 2g), which is possibly caused by the fact that satellites can detect sub-visible cirrus clouds, but observers do not (Bedacht et al. 2007). Moreover, the disparity of measurements or inhomogeneity collection of data in ICOADS can partly explain this difference.

3.2 Seasonal cycle

The ECSK lies in the East Asian monsoon region, where the oceanic and atmospheric conditions are highly dependent on the seasonal variation of the East Asian monsoon. As shown in Figs. 3a–d, 3m–p, and 4, all cloud products capture the evident seasonal variation of LCA, with the peak in winter and the valley in summer. Following Wood and Bretherton (2006), an index, estimated inversion strength (EIS), is calculated as follows:

\[ \text{EIS} = \text{LTS} - \Gamma_{850}^{\text{m}} (Z_{700} - \text{LCL}), \]

where lower-tropospheric stability (LTS) is the potential temperature difference between 700 hPa and the surface. \( \Gamma_{850}^{\text{m}} \) is the moist adiabatic lapse rate at 850 hPa, \( Z_{700} \) is the altitude of the 700 hPa level, and LCL is the height of lifting condensation level. The EIS index is used to estimate the stability of the lower troposphere, i.e., a larger EIS implies a stronger inversion layer. The difference of surface air temperature at 2 m (SAT) and SST (SAT – SST) is defined as an index of stability of the air–sea interface.

In winter, a larger LCA is forced by strong surface heat and moisture flux and maintained by strengthened EIS (Figs. 3a, e, i). As shown in Figs. 3a and 3e, a large negative SAT – SST is conducive to strong turbulence in air–sea interface when cold air blows from the East Asian continent to the warm ocean surface in the East China Sea and Yellow Sea, especially across the strong SST front over the Kuroshio. Stable lower atmospheric stability associated with relatively strong mid-tropospheric subsidence confines the clouds at low levels, resulting in higher low cloud amounts (Figs. 3i, m). In spring and summer, frequent
convection denoted by the upward motion in Figs. 3j and 3k due to the seasonal march of the Mei-Yu front is in favor of middle and/or high clouds (Figs. 3n, o), corresponding to a larger TCA (Fig. 4). Previous studies have indeed discussed the seasonality and various formation mechanisms of low clouds on both regional and global scales (e.g., Klein and Hartmann 1993; Young and Sikora 2003; Tokinaga et al. 2009). On the basis of the seasonal dependence of the cloud amount, intercomparisons of CA are conducted below.

Fig. 3. Seasonal cycle of (a–d) LCA (%), shading) and SST (K, interval 1 K, contours); (e–h) SAT − SST (K, shading), SLP (hPa, contours), and horizontal wind at 1000 hPa (m s\(^{-1}\), vectors); (i–l) EIS (K, shading), omega (−0.01 Pa s\(^{-1}\), contours), and horizontal wind at 700 hPa (m s\(^{-1}\), vectors); (m–p) vertical distribution of cloud amount (%), shading), averaged from 124°E to 126°E.
for different seasons.

\textbf{a. Low cloud amount (LCA)}

The difference in LCA between MODIS (CALIPSO) and CC varies between 3–9% (−24 to −17%) during winter to about 20–22% (−12 to 0.2%) in summer (Fig. 4). This is similar to the work of Kay and Gettelman (2009), who compared the datasets near the marginal seas in the Arctic Ocean. This implies a systematical bias between each product and CC. The possible reasons for the positive (negative) bias in MODIS (CALIPSO) are mentioned above. As shown in Figs. 3i and 3j, the inversion layer is stronger and more frequent in winter and spring than in summer and fall. In the presence of the strong inversion layer, MODIS tends to underestimate LCA (Holz et al. 2008; Hagihara et al. 2010), which offsets somewhat the positive bias resulting from the reasons mentioned above. In contrast, the LCA derived from ICOADS tends to be underestimated approximately by 8% in winter and overestimated by about 14% in summer. This bias between ICOADS and CC is probably related to the difference in the definition of low cloud types in this work and also the temporal and spatial inhomogeneity of sampling (Norris 1998b; Bedacht et al. 2007).

For the LCA distribution, almost all products present a cloud band along the Kuroshio SST front in cold seasons (i.e., DJF, MAM, and SON; Fig. 5). A similar low cloud regime transition occurs over subtropical regions with increasing SST, which is called the “deepening-warming decoupling mechanism” (Bretherton and Wyant 1997; Skyllingstad and Edson 2008; Liu et al. 2016). The spatial pattern correlation in LCA between MODIS and CC is higher than that between either CALIPSO or ICOADS and CC in all seasons. Note that the LCA from ICOADS shows spatial patterns in good agreement with that from CC in both winter and fall. This strongly suggests that ICOADS is a good reference data for climate research in this region and also for other regions as indicated in some previous studies (Norris 1998a, b; Clement et al. 2009).

Figure 6 shows the scatter diagrams of LCA from CALIPSO, MODIS, and ICOADS against that from CC. We can see that the LCA from MODIS is well correlated with that from CC, especially in SON, with a correlation coefficient of 0.77. However, the systematic bias of MODIS in any of the seasons is more evident than that of either CALIPSO or ICOADS, which can be seen from the STDD of around 10% (Table 3). Moreover, the frequency distribution in Fig. 6 shows that more than 60% of the differences are in the range of 0–20% (with a mean bias of 10%), indicating a small and concentrated bias of MODIS. Except in fall, the distributions of LCA from both CALIPSO and ICOADS are either dispersive or random, which is reflected in the low linear correlation and large STDD in comparison with MODIS. The RMSE decreases as the bias (correlation coefficient) decreases (increases) in the datasets, which is similar to the results of Kotarba (2009, 2015). The seasonal variation of disparity is primarily associated with the changes in cloud types. Owing to less influence from upper-level clouds due to a relatively strong inversion layer in fall (Fig. 3i), MODIS and CALIPSO tend to detect LCA more precisely than in winter, spring, and summer, in which deep and high clouds are frequently induced by the SST frontal forcing (Figs. 3a, b) and/or the Mei-Yu front (Figs. 3j, k). As for ICOADS, the difference is associated with the definition of low cloud types and sampling inhomogeneity (Norris 1998b; Bedacht et al. 2007).

Overall, the agreement of LCA between MODIS and CC is the best among all products, despite relatively large systematic biases. The ICOADS can be a good reference for the climatological mean LCA. The products are capable of providing relatively accurate measurements in cold seasons but not good in summer.

\textbf{b. Total cloud amount (TCA)}

The TCA derived from CC reaches its peak (83%) in June and its valley (62%) in August (Fig. 4). The TCA obtained from ICOADS presents a large negative difference in summer because of sub-visible cirrus clouds. Globally, CAs reported by surface observers are frequently larger than those detected by satellites (Kotarba 2009), and surface observers tend to report
Fig. 5. Climatologically seasonal mean LCA (shading) derived from CC (a–d), CALIPSO (e–h), MODIS (i–l), and ICOADS (m–p) in DJF, MAM, JJA, and SON, respectively. Climatologically seasonal mean SST shown in each row (black contours with an interval of 1°C. Bold contours donate 20°C and 24°C). The spatial correlation coefficient between CC and each dataset of CMI is shown at the bottom right of each panel. The black coefficient (r) means over 95% confidence level.
smaller CAs over Europe (Kriebel et al. 2003), which is similar to our comparison in the ECSK region. The difference between each dataset of CMI and CC ranges from 1 to 15% in winter and −25 to −4% in summer, which implies that the systematic biases are consistently smaller in winter than in summer.

Figure 7 shows a cloud band (with high TCA) along the Kuroshio SST front in all products in cold seasons. The TCA in summer shows higher values in the Yellow Sea and lower values over the ECSK. A comparison of the spatial distribution of TCA in Fig. 7 with the seasonal variation of LCA in Fig. 5 indicates that the LCA largely contributed to the TCA in this region. The agreement in the spatial pattern of TCA increased significantly compared with that of LCA. MODIS tends to give a slightly larger TCA than the other datasets, with the averaged value from 69% in summer to 81% in winter. This is probably due to the relatively coarse grid (0.5 km) in comparison with CALIPSO (333 m) (Hagihara et al. 2010; Pincus et al. 2012). Assuming that in a 10 × 10 km box, when a single liquid water cloud with a radius of 0.5 km sur-

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Fig. 6. Scatter diagrams of LCA between two datasets in DJF (a–c), MAM (e–g), JJA (i–l), and SON (n–p). Each single dot represents a comparison of monthly cloud amounts at a single grid in four years; the corresponding frequency distribution for the LCA difference of each of the CMI datasets and CC is shown in the rightmost column (d, h, m, and q).
rounded by clear sky is detected in a box with a horizontal resolution of 2.5 × 2.5 km, TCA is calculated as 1/16. Although the cloud is detected in a coarser grid (e.g., 5 × 5 km), 1/4 of TCA is reported. Therefore, the cloud amount derived from horizontal averaging can induce an artificial overestimate in broken cumulus fields. The overestimate ranges up to about 20–25% in the trade cumulus regime (Chepfer et al. 2010).

Fig. 7. The same as Fig. 5 but for TCA.
Moreover, the fact that satellites may detect thin cirrus not seen by surface observers (Bedacht et al. 2007) can also result in the overestimate of TCA. The seasonal mean bias in TCA from CALIPSO relative to that from CC is less than 10%, suggesting a small contribution of CPR to TCA detection. The amplitude of TCA given by ICOADS is similar to that given by CC and CALIPSO, especially in winter with a spatial correlation coefficient of 0.71. Comparing the seasonal mean TCA, MODIS and CALIPSO can provide a more accurate TCA in winter and spring, whereas ICOADS is only good in winter.

The scatter diagrams in Fig. 8 show that the correlation in TCA derived from CALIPSO and MODIS is much stronger than that in LCA. The agreement tends to be better in summer than in cold seasons. MODIS shows higher correlation coefficients in TCA with CC in all seasons (Figs. 8b, f, j, o) than either CALIPSO and ICOADS, with the mean biases varying from -1.5% in summer to 13.2% in winter (Figs. 8d, h, m, q). Relatively small STDDs indicate a systematic bias between MODIS and CC in all seasons (Table 3). The correlation coefficients (STDDs) in TCA between CALIPSO and CC are larger (smaller) than those in.
LCA in all seasons (Fig. 6), implying the high similarity of CALIPSO and CC. Moreover, biases in TCA from CALIPSO relative to that from CC shift from positive in summer to negative in early fall, which is probably due to the high occurrence frequency of deep convective clouds. This is because CALIPSO is insensitive to convective clouds with large optical thickness (Kay and Gettelman 2009; Chan and Comiso 2013). The poor correlation between ICOADS and CC in Fig. 8 indicates that ICOADS is good only in winter for the TCA assessments (Fig. 7d). Therefore, CALIPSO and MODIS can provide a competitive description of TCA in all seasons, whereas ICOADS is good in winter only.

3.3 Interannual variability

A long-term dataset is important for studies of cloud variability, such as the interannual and interdecadal variabilities and the potential changes under global warming (Norris and Leovy 1994; Clement et al. 2009; Eastman et al. 2011). To assess the accuracy of relatively long-term cloud datasets (e.g., MODIS and ICOADS, with their time spans listed in Table 1), their CAs are averaged in the ECSK and compared with that of CC in the period of 2007–2010 in Fig. 9. Owing to limited records available, we first define the trend between two adjacent years for each product and compare it with the corresponding trend obtained from CC. The ratio of the trends from each of the products to that from CC is defined as the Matching Score (MS). In this way, an MS of 1.0 means a good agreement in interannual variability between this product and CC. Here we mainly focus on the long-term products, namely, MODIS and ICOADS during 2003–2014 (Fig. 9).

a. Low cloud amount (LCA)

We can see from Figs. 9a–d that the interannual variation in LCA from MODIS is quite consistent with that from CC in cold seasons, with an MS of 1.0. The interannual variation in LCA from ICOADS also matches well with that of CC in winter (MS of 1.0), with a high agreement with CC in spring with an MS of 2/3, but poor in both summer and fall. For a longer period comparison (Figs. 9a–d), MODIS and ICOADS show similar interannual variations of LCA in both winter and spring, with correlation coefficients of 0.49 and 0.55, respectively. The covariations of the two datasets in winter and spring imply a mutual support of their usefulness for the studies of climate
variability in LCA in both seasons in the region. A prominent increasing trend in LCA appears in fall in the two products (Fig. 9d). After removing the trend, the correlation between the two products decreases significantly from 0.65 to 0.24 in fall, indicating that MODIS and ICOADS show inconsistent interannual variability of LCA in fall. Moreover, it seems that CMI datasets are greatly diverse in depicting the interannual variation of LCA in summer, similar to the diversity in the climatological seasonal variation (Figs. 5, 6).

b. Total cloud amount (TCA)

Similar to that of LCA, the interannual variation of TCA from MODIS is in good agreement with that from CC in all seasons, with an MS of 1.0 from winter to summer and 2/3 in fall (Figs. 9e–h). ICOADS shows an interannual variation of TCA consistent with that of CC in winter and spring with MSs of 1 and 2/3, respectively. This is consistent with the results of the climatological seasonal variation as well (Figs. 7, 8). MODIS and ICOADS in the longer period show correlation coefficients from 0.6 in winter to 0.7 in spring, both higher than that of LCA (Figs. 10a–d). This suggests that, although different approaches yield different monthly local CA, they are expected to give similar interannual variabilities of the averaged CA in particular seasons (Wu et al. 2014).

c. Two dominant modes of TCA in spring derived from MODIS and ICOADS

In order to examine the reliability of interannual variation in CA obtained from different cloud products, here we compare the dominant modes of CA and assess the relationship between CA and the atmospheric circulation (e.g., anomalous western North Pacific High–WNPH). On the basis of the results of TCA in spring (Fig. 9f), we calculated the dominant modes of TCA from ICOADS and MODIS using the Empirical Orthogonal Function (EOF) analysis. Figures 10a and 10b (10d and 10e) show spatial patterns corresponding to the first (second) EOF of TCA from ICOADS and MODIS in spring. Figure 10c (10f) displays the behavior of the first (second) normalized principal components (PCs). The first EOF of TCA explains 35% of the total variance in ICOADS and accounts for 47% of the total variance in MODIS. This mode represents a uniform distribution of TCA interannual variation over the ECSK. The first PC of ICOADS is well correlated with that of MODIS, with a correlation coefficient of 0.84, exceeding 99% confidence level. The first PC of TCA is probably associated with the interannual variability of the anomalous WNPH, with their correlation coefficient varying from 0.44 to 0.52. This implies that the anomalous moisture transport from the tropics to the ECSK associated with anticyclonic (cyclonic) circulation probably facilitates (damps) TCA. The second EOF of TCA shows a
dipole structure between the Yellow Sea and the East China Sea, accounting for 18.7% of the total variance in ICOADS and for 25% in MODIS. The second PC also presents a good agreement in interannual variation between the two products, with a correlation coefficient of 0.56 over 95% confidence level.

The results of the EOF analysis demonstrate similar spatial distributions and interannual variabilities of spring TCA in MODIS and ICOADS. As an indirect implication, the link between TCA and the large-scale atmospheric circulation confirms that TCA in spring from MODIS and ICOADS can be used to depict the TCA interannual variation in spring by these two TCA products in further studies.

4. Summary

The cloud variability and regime transition from stratocumulus to cumulus across the SST front in the ECSK region are important regional climate features and can affect the Earth's energy balance. However, large uncertainties exist among available cloud products. It is unclear which cloud datasets are more reliable for use in studying the cloud features or in validating climate model cloud simulations in the region. In this study, we performed an assessment of the most representative cloud datasets, including ICOADS, MODIS, and CALIPSO, based on the CC dataset in the ECSK and intercompared the dominant modes of variability of cloud amounts derived from ICOADS and MODIS.

Both LCA and TCA products derived from different platforms (i.e., marine surface observation and active and passive remote sensing from satellites) in the Kuroshio region over the East China Sea (ECSK) from December 2006 to November 2010 have been compared in this study. The combined products based on CloudSat and CALIPSO (CC) were treated as the baseline to assess other products because of their relatively high quality but short record (four years only).

The linear correlation coefficient (R), mean difference (Bias), STDD, and RMSE were used as metrics to quantify the quality of these datasets.

The results show that MODIS and CALIPSO generally present highly consistent climatological annual means with CC in both LCA and TCA. On seasonal time scale, the agreement in LCA between each product and CC is generally good in cold seasons (i.e., winter, spring, and fall) but poor in summer. The LCA obtained from MODIS shows the highest spatial correlation with that obtained from CC, especially in fall with a correlation coefficient of 0.77, despite a systematic bias ranging from 6.83% in winter to 21.54% in summer relative to CC. The spatial correlation in the seasonal mean LCA between ICOADS and CC is large in winter and fall even though the correlation looks poor in the scatter diagrams. This indicates that ICOADS can be a good reference dataset to the study of the annual and seasonal mean LCAs, consistent with the finding of Wu et al. (2014). The correlation in TCA between any of the other three datasets and CC is generally stronger than that of LCA. CALIPSO presents a much better agreement with that from CC because of their similar instruments in TCA detection. MODIS can also provide a competitive description of TCA, whereas ICOADS is good in terms of the climatological seasonal mean TCA in winter only.

On the interannual time scale, both MODIS and ICOADS show similar qualities in both TCA and LCA estimates in winter and spring. Further EOF analysis for spring TCA indicates that the spatial and temporal properties of TCA derived from ICOADS are in good agreement with those from MODIS. The major interannual variability patterns in spring, such as the anomalous western North Pacific high (WNPH), are well captured in both ICOADS and MODIS TCA products. Moreover, the link between the first EOF and anomalous WNPH implies a possible mechanism that anomalous WNPH controls largely the interannual variability of TCA over the ECSK and even a possible impact of El Niño–Southern Oscillation on TCA in the region. This link provides a support to the reliability of spring TCA from the two products for the study of interannual variation as well.

In summary, our results indicate a relatively good agreement in both LCA and TCA obtained from MODIS with those from CC in winter, spring, and fall on both annual and seasonal time scales. On interannual time scale, LCA (TCA) in ICOADS and MODIS is highly consistent in winter and spring, suggesting that the relatively long record LCA (TCA) averaged over the ECSK can be used to study the interannual climate variability in the region. Results from this study provide a good reference for the study of clouds in the ECSK region and are also helpful for the validation of cloud simulations in the region by climate models.

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