

1 **Cloud climatologies from the InfraRed Sounders AIRS and IASI:** 2 **Strengths and Applications**

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11 **Abstract**

12 Global cloud climatologies have been built from 13 years of Atmospheric IR Sounder (AIRS) and 8
13 years of IR Atmospheric Interferometer (IASI) observations, using an updated Clouds from IR Sounders
14 (CIRS) retrieval. The CIRS software can handle any Infrared (IR) sounder data. Compared to the
15 original retrieval, it uses improved radiative transfer modelling, accounts for atmospheric spectral
16 transmissivity changes associated with CO₂ concentration and incorporates the latest ancillary data
17 (atmospheric profiles, surface temperature and emissivities). The global cloud amount is estimated to
18 0.67 ± 0.03, for clouds with IR optical depth larger than about 0.1. The spread of 0.03 is associated with
19 ancillary data. Cloud amount is partitioned into about 40% high-level clouds, 40% low-level clouds and
20 20% mid-level clouds. The latter two categories are only detected in the absence of upper clouds. The A-
21 Train active instruments, lidar and radar of the CALIPSO and CloudSat missions, provide a unique
22 opportunity to evaluate the retrieved AIRS cloud properties. CIRS cloud height can be approximated
23 either by the mean layer height (for optically thin clouds) or by the mean between cloud top and the
24 height at which the cloud reaches opacity. This is valid for high-level as well as for low-level clouds
25 identified by CIRS. IR sounders are particularly advantageous to retrieve upper tropospheric cloud
26 properties, with a reliable cirrus identification, day and night. These clouds are most abundant in the
27 tropics, where high opaque clouds make out 7.5%, thick cirrus 27.5% and thin cirrus about 21.5% of all
28 clouds. The 5% annual mean excess in high-level cloud amount in the Northern compared to the
29 Southern hemisphere has a pronounced seasonal cycle with a maximum of 25% in boreal summer, in
30 accordance with the moving of the ITCZ peak latitude, with annual mean of 4°N, to a maximum of

1 12°N. This suggests that this excess is mainly determined by the position of the ITCZ. Considering
2 interannual variability, tropical cirrus are more frequent relative to all clouds when the global (or tropical)
3 mean surface gets warmer. Changes in relative amount of tropical high opaque and thin cirrus with
4 respect to mean surface temperature show different geographical patterns, suggesting that their response
5 to climate change might differ.

6 **1 Introduction**

7 Clouds cover about 70% of the Earth's surface and play a key role in the energy and water cycle of our
8 planet. The Global Energy and Water Exchanges (GEWEX) Cloud Assessment (Stubenrauch *et al.*,
9 2013) has highlighted the value of cloud properties derived from space observations for climate studies
10 and model evaluation and has identified reasons for discrepancies in the retrieval of specific scenes, in
11 particular thin cirrus, alone or with underlying low-level clouds. Compared to other passive remote
12 sensing instruments, the high spectral resolution of IR vertical sounders leads to especially reliable
13 properties of cirrus, with IR optical depth as low as 0.1, day and night. Channels varying in CO₂
14 absorption are used to determine height and emissivity of a single cloud layer, which corresponds to the
15 uppermost cloud layer in the case of multiple cloud layers. While measured radiances near the center of
16 the CO₂ absorption band are only sensitive to the upper atmosphere, radiances from the wing of the band
17 are emitted from successively lower levels in the atmosphere.

18 Spaceborne IR sounders have been observing our planet since the 1980s: the High Resolution Infrared
19 Radiation Sounders (HIRS) aboard the National Oceanic and Atmospheric Administration (NOAA)
20 polar satellites provide data since 1979, the Atmospheric InfraRed Sounder (AIRS) aboard the National
21 Aeronautics and Space Administration (NASA) Earth Observation Satellite Aqua since 2002, the IR
22 Atmospheric Sounding Interferometers (IASI) aboard the European Organisation for the Exploitation of
23 Meteorological Satellites (EUMETSAT) Meteorological Operation (MetOp) since 2006 and the Cross-
24 track Infrared Sounder (CrIS) aboard the Suomi National Polar-orbiting Partnership (NPP) satellite since
25 2011. A next generation of IR sounders (IASI-NG) is foreseen as part of the EUMETSAT Polar System
26 2 Second Generation (EPS-SG) program for 2021 (Crevoisier *et al.*, 2014).

27 Active sensors are part of the A-Train satellite formation (Stephens *et al.*, 2002), synchronous with
28 Aqua, since 2006: The CALIPSO lidar and CloudSat radar, together, are capable of observing the cloud
29 vertical structure (e.g. Henderson *et al.*, 2013; Mace and Zhang, 2014). Whereas the lidar can detect sub-
30 visible cirrus, its beam can only penetrate the cloud down to optical depth of about 3 to 5 (in visible
31 range). For optically thicker clouds, the radar provides the cloud base.

1 Our goal to establish a coherent long-term cloud climatology from different IR sounders has led to the
2 evolution of the original LMD cloud retrieval method (Stubenrauch *et al.*, 1999, 2006, 2008, 2010)
3 towards an operational and modular cloud retrieval algorithm suite (CIRS, Feofilov and Stubenrauch,
4 2017). The CIRS retrieval has so far been applied to AIRS and IASI data as well as to HIRS data
5 (Hanschmann *et al.*, 2017). The cloud property retrieval employs radiative transfer modelling and
6 atmospheric and surface ancillary data (atmospheric temperature and water vapour profiles, surface
7 temperature and surface emissivity, identification of snow and ice). Compared to the original retrieval,
8 the CIRS retrieval applies improved radiative transfer calculations and a novel calibration method,
9 accounting for latitudinal, seasonal and interannual atmospheric CO₂ variations, which adjusts the
10 atmospheric spectral transmissivity look-up tables.

11 The 6-year AIRS-LMD cloud climatology (Stubenrauch *et al.*, 2010) participated in the GEWEX Cloud
12 Assessment. In this article, we present the results of i) an updated and extended 13-year AIRS cloud
13 climatology (2003 ó 2015), using two different sets of the latest ancillary data (originating from retrievals
14 and from meteorological reanalyses), and ii) a new 8-year IASI cloud climatology (2008 ó 2015). After
15 the description of data and methods in section 2, section 3 is dedicated to the evaluation of cloud
16 detection and cloud height using the unique A-Train synergy of synchronous passive and active
17 measurements. Section 4 presents average cloud properties and their regional, seasonal, inter-annual and
18 long-term variability, in comparison with other datasets, as well as uncertainty estimates with respect to
19 the used ancillary data. Section 5 concentrates on the variability of the upper tropospheric clouds with
20 respect to changes in atmospheric conditions in order to illustrate how these data may be used for climate
21 studies. Conclusions and an outlook are given in section 6.

22 **2 Data and methods**

23 **2.1 AIRS Data**

24 The AIRS instrument (Chahine *et al.*, 2006) provides very high spectral resolution measurements of
25 Earth emitted radiation in 2378 spectral bands in the thermal infrared (3.74-15.40 μm). The spatial
26 resolution of these measurements varies from 13.5 km x 13.5 km at nadir to 41 km x 21 km at the scan
27 extremes. The polar orbiting Aqua satellite provides observations at 1:30AM and 1:30PM local time
28 (LT). Nine AIRS measurements (3 x 3) correspond to one footprint of the Advanced Microwave
29 Sounder Unit (AMSU), grouped as a golf ball

30 The CIRS cloud retrieval uses measured radiances along the wing of the 15 μm CO₂ absorption band.
31 We have chosen AIRS channels closely corresponding to the five channels used in the TIROS-N
32 Operational Vertical Sounder (TOVS) Path-B cloud retrieval, at wavelengths of 14.19, 14.00, 13.93,

1 13.28 and 10.90 μm , and three additional channels at 14.30, 14.09 and 13.24 μm (with peaks in the
2 weighting function at 235, 255, 375, 565, 415, 755, 885 hPa and surface, respectively). The multi-
3 spectral cloud detection, based on the spectral coherence of retrieved cloud emissivities, decides whether
4 the AIRS footprint is cloudy (section 2.5.3). For the latter, radiances in the atmospheric window
5 between 9 and 12 μm are used, at six wavelengths of 11.85, 10.90, 10.69, 10.40, 10.16, 9.12 μm .

6 Ancillary data necessary for the cloud retrieval, which include atmospheric temperature and water
7 vapour profiles as well as surface skin temperature, are provided by the NASA Science Team L2
8 standard products (Version 6 (V6); Olsen *et al.*, 2017). They were retrieved from cloud-cleared AIRS
9 radiances within each AMSU footprint. The methodology remains essentially the same as described in
10 Susskind *et al.* (2003). Compared to Version 5 (V5), the most significant changes are: i) V6 uses an IRó
11 microwave neural network solution (Blackwell *et al.*, 2014) as a first guess for the retrieval of
12 atmospheric temperature and water vapour profiles as well as for surface skin temperature, instead of the
13 previously used regression approach (Susskind *et al.*, 2014). This leads to physical solutions for many
14 more cases than in V5. ii) The retrieval of surface skin temperature only uses shortwave IR window
15 channels (Susskind *et al.*, 2014). These modifications resulted in significant improvement of accurate
16 temperature profiles and surface skin temperatures under partially cloudy conditions (Van T. Dang *et al.*,
17 2012): Compared to V5, the surface skin temperature is larger over land in the afternoon (especially over
18 desert) and over maritime stratocumulus regions.

19 In addition, we use the microwave identification of snow or ice covered surfaces, also provided by the
20 NASA L2 data.

21 Since the retrieved cloud pressure should be within the troposphere / lower stratosphere, we have
22 determined the tropopause pressure from the atmospheric profiles, using the concept described in
23 Reichler *et al.* (2003) and in Feofilov and Stubenrauch (2017). The CIRS cloud retrieval allows cloud
24 levels up to 30 hPa above the tropopause.

25 **2.2 IASI data**

26 IASI, developed by CNES in collaboration with EUMETSAT, is a Fourier Transform Spectrometer
27 based on a Michelson interferometer, which covers the IR spectral domain from 3.62 to 15.5 μm . As a
28 cross-track scanner, the swath corresponds to 30 ground fields per scan, each of these measures a 2×2
29 array of footprints. The latter have a 12-km diameter at nadir. IASI raw measurements are interferograms
30 that are processed to radiometrically calibrated spectra on board the satellite. Two instruments were
31 launched so far onboard the European Platforms Metop-A and Metop-B (in October 2006 and
32 September 2012, respectively), with measurements at 9:30AM / 9:30PM LT and 10:30AM / 10:30PM

1 LT (local equator crossing time). IASI has been providing water vapour and temperature sounding
2 profiles for operational meteorology (accuracy requirements respectively of 1 K and 10% in the
3 troposphere), as well as trace gas concentrations, surface and atmospheric properties, including those of
4 aerosols and clouds (Hilton *et al.*, 2012). For the cloud retrieval, we use radiances at the wavelengths
5 14.30, 14.20, 14.06, 14.00, 13.93, 13.40, 13.24 and 10.90 μm , and for the multi-spectral cloud detection
6 the radiances at 11.85, 10.90, 10.70, 10.41, 10.16, and 9.13 μm .

7 At the time we started incorporating IASI data to the CIRS cloud retrieval, two data sets of IASI-
8 retrieved atmospheric profiles and surface temperature were available: one provided by EUMETSAT
9 (Version 5) and one by NOAA. EUMETSAT L2 temperature and water vapour Version 5 products
10 were only available for clear and partly cloudy scenes, leaving atmospheric and surface retrievals in only
11 9% of all cases. Therefore we first used IASI L2 ancillary data provided by NOAA. The comparison
12 with collocated temperature profiles of the Analyzed RadioSoundings Archive (ARSA, available at the
13 French data centre AERIS) has shown that, while AIRS-NASA and ERA-Interim (section 2.3)
14 temperature profiles do agree in general with the ARSA profiles within 1 K, differences between IASI-
15 NOAA and ARSA profiles were often larger than 1 K in the lower troposphere (not shown). In addition,
16 a study of the influence of the different ancillary data on the CIRS cloud amount has demonstrated that
17 the amount of low-level clouds over ocean was underestimated, when using those deduced from IASI-
18 NOAA (Feofilov *et al.*, 2015a). This might be explained by an underestimation of the sea surface
19 temperature (SST) linked to cloud contamination. From this we concluded, that the AIRS ó IASI
20 synergy to explore cloud diurnal variability in a coherent way needs ancillary data from similar retrievals
21 or from the same source. Thus we also implemented ancillary data from the European Centre for
22 Medium-Range Weather Forecasts (ECMWF) meteorological reanalyses into the CIRS cloud retrieval.

23 **2.3 ERA-Interim meteorological reanalyses**

24 ECMWF provides the meteorological reanalyses ERA-Interim, covering the period from 1989 until
25 now. Dee *et al.* (2011) give a detailed description of the model approach and the assimilation of data.
26 The data assimilation scheme is sequential: at each time step, it assimilates available observations to
27 constrain the model, which then provides a short-range forecast for the next assimilation time step.
28 Gridded data products (at a spatial resolution of 0.75° latitude x 0.75° longitude) include 6-hourly surface
29 temperature, atmospheric temperature and water vapour profiles, as well as dynamical parameters such
30 as horizontal and vertical large-scale winds. These data are given at universal time of 0:00, 6:00, 12:00
31 and 18:00. To match these data with the AIRS and IASI observations, we interpolate them to the
32 corresponding local time, using a cubic spline function, as in Aires *et al.* (2004).

1 **2.4 Collocated AIRS & CALIPSO & CloudSat data**

2 All satellites of the A-Train follow each other within a few minutes. We use the same collocation
3 procedure as in Feofilov *et al.* (2015b): First, each AIRS footprint is collocated with NASA CALIPSO
4 L2 cloud data averaged over 5 km (version 3, Winker *et al.*, 2009) in such a way that for each AIRS golf
5 ball, three CALIPSO samples are matched to the centres of three AIRS footprints. These data are then
6 collocated with the NASA L2 CloudSat-lidar geometrical profiling (GEOPROF) data (version R04,
7 Mace and Zhang, 2014). Each of these AIRS footprints thus includes cloud top and cloud base for each
8 of the cloud layers, detected by lidar or radar, at the spatial resolution of the radar footprints (1.4 km x 2.3
9 km) from the GEOPROF data. Cloud optical depth (COD), cloud top, z_{top} , and apparent cloud base
10 (corresponding to the real cloud base or to the height at which the cloud reaches opacity), $z_{app\ base}$, are
11 given at the spatial resolution of the CALIPSO cloud data (5 km x 0.09 km). A cloud feature flag
12 indicates whether the cloud is opaque. The CALIPSO cloud data also indicate at which horizontal
13 averaging along the track the cloud was detected (1 km, 5 km or 20 km), which is a measure of the
14 COD. As in Stubenrauch *et al.* (2010), for a direct comparison with AIRS cloud data, we use clouds
15 detected at horizontal averaging over 5 km or less. This corresponds to clouds with visible COD larger
16 than about 0.05 to 0.1 (Winker *et al.*, 2008).

17 The scene type of an AIRS footprint is estimated as cloudy when the CALIPSO sample as well as the
18 GEOPROF sample include at least one cloud layer. Clear sky is defined by cloud-free CALIPSO and
19 GEOPROF samples within the AIRS footprint.

20 For the evaluation of cloud height, we identify the GEOPROF cloud layer which is closest to z_{cl} from
21 AIRS and estimate the height at which the cloud reaches a COD of 0.5, $z_{COD0.5}$, from CALIPSO. $z_{COD0.5}$
22 is required to be located within the corresponding GEOPROF cloud layer. $z_{COD0.5}$ is deduced from the
23 CALIPSO L2 COD, assuming a constant increase of COD from cloud top towards cloud base, except
24 for high-level clouds, for which the shape of the ice water content profile as a function of cloud
25 emissivity is taken into account (Feofilov *et al.*, 2015b). As the COD of CALIPSO might be slightly
26 underestimated (Lamquin *et al.*, 2008), especially for larger COD, we reduce the ratio 0.5/COD to
27 0.4/COD, used in the estimation of $z_{COD0.5}$.

28 **2.5 CIRS cloud property retrieval**

29 The cloud property retrieval is based on a weighted χ^2 method using channels along the wing of the 15
30 μm CO₂ absorption band (Stubenrauch *et al.*, 1999). Cloud pressure and effective emissivity are
31 determined by minimizing $\chi^2(p_k)$, computed at different atmospheric pressure levels by summation over
32 N wavelengths λ_i :

$$1 \quad \chi^2(\mathbf{p}_k) = \sum_{i=1}^N \left[(\mathbf{I}_{cld}(\mathbf{p}_k, \lambda_i) - \mathbf{I}_{clr}(\lambda_i)) \cdot \varepsilon_{cld}(\mathbf{p}_k) - (\mathbf{I}_m(\lambda_i) - \mathbf{I}_{clr}(\lambda_i)) \right]^2 \cdot \mathbf{W}^2(\mathbf{p}_k, \lambda_i) \quad (1)$$

2 I_m corresponds to the measured radiance. I_{clr} is the simulated radiance the IR Sounder would measure in
3 the case of clear sky, and $I_{cld}(p_k)$ is the radiance emitted by a homogeneous opaque single cloud layer at
4 pressure level p_k . I_{cld} is calculated for 42 p_k levels (from 984 hPa to 86 hPa), for the viewing zenith angle
5 of the observation. A sensitivity study has shown that five (for HIRS) to eight channels (AIRS and IASI)
6 are sufficient, as doubling the number of channels in the retrieval did not change the results.
7 By introducing empirical weights $W(p_k, \lambda_i)$, the method takes into account i) the vertical
8 contribution of the different channels, ii) the growing uncertainty in the computation of ε_{cld}
9 with increasing p_k and iii) uncertainties in atmospheric profiles. These weights are determined
10 for each of five typical air mass classes (tropical, midlatitude summer and winter, polar
11 summer and winter) as in Stubenrauch *et al.* (1999) and in Feofilov and Stubenrauch (2017),
12 using the spread of clear sky radiances within these air mass classes. The clear sky radiances
13 have been simulated for each of the atmospheric profiles of these five air mass classes, using
14 the 4A radiative transfer model (Scott and Chédin, 1981), and stored in the Thermodynamic
15 Initial Guess Retrieval (TIGR) data base (Chédin *et al.*, 1985; Chevallier *et al.*, 1998; Chédin
16 *et al.*, 2003). Minimizing χ^2 in Eq. 1 is equivalent to $d\chi^2/d\varepsilon_{cld} = 0$, from which one can
17 extract ε_{cld} as:

$$18 \quad \varepsilon_{cld}(\mathbf{p}_k) = \frac{\sum_{i=1}^N [\mathbf{I}_m(\lambda_i) - \mathbf{I}_{clr}(\lambda_i)] \cdot [\mathbf{I}_{cld}(\mathbf{p}_k, \lambda_i) - \mathbf{I}_{clr}(\lambda_i)] \cdot \mathbf{W}^2(\mathbf{p}_k, \lambda_i)}{\sum_{i=1}^N [\mathbf{I}_{cld}(\mathbf{p}_k, \lambda_i) - \mathbf{I}_{clr}(\lambda_i)]^2 \cdot \mathbf{W}^2(\mathbf{p}_k, \lambda_i)} \quad (2)$$

19 In general, the $\chi^2(p)$ profiles have a more pronounced minimum for high-level clouds than for low-level
20 clouds. We stress here that for the identification of low-level clouds it is important to allow values larger
21 than 1 for ε_{cld} , because at larger pressure I_{clr} and I_{cld} become very similar and their uncertainties may lead
22 to values larger than 1 (Stubenrauch *et al.*, 1999). Thus only pressure levels leading to $\varepsilon_{cld} > 1.5$ are
23 excluded from the solution. Typical p_{cld} uncertainties have been estimated from a statistical analysis of
24 the $\chi^2(p)$ profiles: they range from 30 hPa for high-level clouds to 120 hPa for low-level clouds,
25 corresponding to about 1.2 km in altitude, z_{cld} .

26 In the case of atmospheric temperature inversions in the lower troposphere, the cloud height is moved to
27 the inversion level, z_{inv} , defined as the highest level with $T(z_{inv}) > T_{surf}$. To detect these cases, the inversion
28 strength, defined by $T(z_{inv}) - T_{surf}$, has to be larger than 2 K. Depending on the ancillary data, these cases

1 occur in about 7 to 15 % of all cloudy cases. ϵ_{cld} as defined in Eq. (2) does not have a physical meaning
2 in the case of an inversion, since $I_{cld}(p_{cld})$ will be greater than I_{clr} . Therefore, we scale ϵ_{cld} and the spectral
3 emissivities in accordance with the ratio p_{inv} / p_{cld} .

4 Cloud temperature, T_{cld} , is determined from p_{cld} , using the ancillary temperature profile similar to the
5 observed situation (see section 2.5.1). Cloud types are distinguished according to p_{cld} and ϵ_{cld} . High-level
6 clouds are defined by $p_{cld} < 440$ hPa, midlevel clouds by $440 \text{ hPa} < p_{cld} < 680$ hPa and low-level clouds
7 by $p_{cld} > 680$ hPa. High-level clouds may be further distinguished into opaque ($\epsilon_{cld} > 0.95$), cirrus ($0.95 >$
8 $\epsilon_{cld} > 0.50$) and thin cirrus ($\epsilon_{cld} < 0.50$). p_{cld} is transformed to cloud altitude, z_{cld} , using a standard
9 hydrostatic conversion.

10 For the computation of I_{clr} and I_{cld} in Eq. (1), we need i) surface type (ocean, land, ice / snow), surface
11 temperature and spectral emissivities, ii) atmospheric temperature and water vapour profiles as well as
12 spectral transmissivity profiles for the atmospheric situation of the measurements. The latter have been
13 calculated using the 4A radiative transfer model, separately for each satellite viewing zenith angle (up to
14 50°) and for about 2300 representative clear sky atmospheric temperature and humidity profiles of the
15 TIGR data base.

16 In the cloud retrieval, the TIGR data base is searched for the atmospheric profile corresponding best to
17 the observational conditions by applying a proximity recognition which compares the atmospheric
18 temperature and water vapour profiles from the ancillary data with those from TIGR as in Stubenrauch
19 *et al.* (2008). The preparation and evaluation of these ancillary data is presented in 2.5.1.

20 *2.5.1 Preparation and comparison of atmospheric / surface ancillary data*

21 *Spectral surface emissivities:* Over land, we use monthly mean spectral surface emissivity climatological
22 values at a spatial resolution of $0.25^\circ \times 0.25^\circ$, retrieved from IASI measurements (Paul *et al.*, 2012). For
23 AIRS, these spectral surface emissivities have been interpolated to the AIRS wavelengths. Over ocean,
24 the surface emissivity is set to 0.99 for $\lambda_i < 10 \mu\text{m}$ and 0.98 for $\lambda_i \times 10 \mu\text{m}$ (Wu and Smith, 1997). Over
25 snow and ice, the spectral surface emissivities are taken from (Hori *et al.*, 2006), and as they depend on
26 the viewing zenith angle, they had to be corrected like in Smith *et al.* (1996).

27 *Atmospheric profiles and surface temperature:* Since IR sounders, in combination with microwave
28 sounders, were originally designed for the retrieval of atmospheric temperature and humidity profiles,
29 the atmospheric clear sky situation can then be directly described by simultaneous L2 atmospheric
30 profiles of good quality. If good quality data are not available for a given measurement, we use 1°
31 latitude \times 1° longitude averages of good quality data. If still no data are available, we interpolate these

1 averages in time (inversely proportional to distance within maximal ± 15 days) and then in space
2 (inversely proportional to distance within maximal 3° longitude, considering the same surface type).

3 To define atmospheric temperature and humidity profiles as well as surface temperature of good quality,
4 one has to find a compromise between an acceptable quality and enough statistics.

5 This led to the following quality criteria in the case of ancillary data from AIRS-NASA (V6):

6 • Surface temperature is of good quality, if the provided retrieval error is smaller than 3 K / 6 K / 7 K for
7 ocean / land / ice or snow, respectively. It should also be larger than 180 K and smaller than 400 K.

8 • Atmospheric temperature profiles are of bad quality, when three consecutive layers have retrieval
9 errors larger than 2 K / 2K / 2K over ocean, 2.5 K / 2.5 K / 3 K over land and 2.5 K / 2.5 K / 5 K over
10 ice or snow, between 70 hPa and 500 hPa / between 500 hPa and surface / near surface, respectively.

11 • For atmospheric water vapour profiles the NASA L2 quality criteria were kept (Olsen *et al.*, 2013).

12 Nevertheless, the SSTs of good quality from AIRS-NASA were still slightly colder than those of ERA-
13 Interim. As this effect is most probably linked to AIRS-NASA residual cloud contamination, we added
14 to the AIRS-NASA SSTs the minimum between the retrieval error and 0.5 K. Since differences over
15 land might be positive or negative (Figure 2), we left the AIRS-NASA surface temperature (T_{surf}) values
16 unchanged.

17 For ERA-Interim, the time-interpolated atmospheric profiles and surface temperatures are always
18 available. However, we found that the time-interpolated ERA-Interim SSTs did not show a diurnal
19 cycle, with most amplitudes less than 0.2 K. As this is not consistent with observations (e.g. Webster *et*
20 *al.*, 1996), we applied a simple parameterized correction, linking the SST diurnal cycle to peak insolation
21 (Webster *et al.*, 1996). The coefficient between the SST diurnal amplitude and the maximal solar flux at
22 given latitude, longitude, solar zenith angle and local time was adjusted to 0.005 K/Wm^2 , so that the
23 SST diurnal amplitude is consistent with recent observations (e.g. Seo *et al.*, 2014). Without this
24 correction, the cloud amount (CA) at night / early afternoon was 78% / 71%, compared to 71% / 71%
25 when using AIRS ancillary data. The correction led to 76% / 73%, closer to the results using AIRS
26 ancillary data. Over land, without changes in T_{surf} , CA at night / early afternoon is 62% / 56%, with
27 ERA-Interim, and 56% / 58%, with AIRS-NASA, respectively.

28 Figure 1 presents comparisons between T_{surf} , as used in the cloud retrieval, deduced from AIRS-NASA
29 and from ERA-Interim, and collocated surface air temperature, T_{surf}^{air} , from the ARSA data base. One
30 would expect that over land T_{surf} is colder than T_{surf}^{air} during night and warmer than T_{surf}^{air} in the
31 afternoon; this effect should be stronger for warmer temperatures, especially if the climate is dry. SST

1 should be similar to T_{surf}^{air} in the tropics, slightly warmer in midlatitudes and colder in polar regions. The
 2 distributions in Figure 1 reflect the expectations, with similar peak positions for AIRS-NASA and ERA-
 3 Interim. Though distributions over land are slightly broader for AIRS-NASA than for ERA-Interim.
 4 They are also shifted towards colder values at night. In the afternoon, T_{surf} of AIRS-NASA is slightly
 5 larger than T_{surf} of ERA-Interim for situations with warm T_{surf} . Colder AIRS-NASA values might still
 6 indicate some cloud contamination, whereas the colder values of ERA-Interim over warm land in the
 7 afternoon might indicate an underestimation, especially over desert, as has already been pointed out by
 8 Trigo *et al.* (2015). The effect of T_{surf} on cloud amount will be further investigated in section 3.1.

9 2.5.2 Accounting for changes in atmospheric CO₂ concentration

10 The TIGR data base of atmospheric spectral transmissivities was created for an atmosphere with a fixed
 11 CO₂ volume mixing ratio of 372 ppmv. However, the atmospheric CO₂ concentration varies
 12 latitudinally, seasonally and with time. Both the increase during the last ten years and the seasonal
 13 variability in the Northern hemisphere (NH) are of the order of ~20 ppmv. The latter is related to the
 14 vegetation and fossil fuel burning seasonality. The difference between an averaged value and actual CO₂
 15 volume mixing ratio can easily reach 10%. This is a noticeable change, as the concentration enters the
 16 power of the exponent in the calculation of the transmissivity, τ . To avoid errors associated with CO₂
 17 changes in the radiative transfer computations, we rescale the transmissivity as:

$$18 \quad \tau = \exp(-\beta - \alpha \cdot CO_2^{current}) \quad (3)$$

19 with $\alpha = -k \cdot \log(\tau^{ref}) / CO_2^{ref}$ and $\beta = \alpha \cdot CO_2^{ref} \cdot \log(1-k) / k$, where k is the relative CO₂
 20 contribution to the opacity of the channel. Details are described in Feofilov and Stubenrauch (2017). The
 21 CO₂ concentrations are taken from (GLOBALVIEW-CO2, 2013).

22 This correction also removes long-term biases due to increasing CO₂ in the atmosphere from
 23 anthropogenic CO₂ emissions, which introduced an artificial increase in the cloud amount time series.
 24 Applying the correction of equation (3) has eliminated this bias (see section 4).

25 2.5.3 Multi-spectral *a posteriori* cloud detection

26 Once the cloud properties are retrieved, to constrain cloud definition, we use the spectral standard
 27 deviation ($\sigma(\lambda_i)$) of retrieved cloud emissivities between 9 and 12 μ m, wavelengths in the IR
 28 atmospheric window, as described in Stubenrauch *et al.* (2010). For each footprint, cloud emissivities ϵ_{cl}
 29 are determined at six wavelengths, λ_i (section 2.1), as:

$$\varepsilon_{cld}(\lambda_i) = \frac{\mathbf{I}_m(\lambda_i) - \mathbf{I}_{clr}(\lambda_i)}{\mathbf{I}_{cld}(\mathbf{p}_{cld}, \lambda_i) - \mathbf{I}_{clr}(\lambda_i)} \quad (4)$$

\mathbf{I}_{cld} is now determined for p_{cld} , retrieved by the χ^2 method (see above).

The relative standard deviation of these cloud emissivities, $(\varepsilon(\lambda_i))/\varepsilon_{cld}$, is much larger when the footprint is partly cloudy or clear and hence p_{cld} is biased, than for cloudy cases, when p_{cld} and ε_{cld} are well determined. This behaviour is illustrated in Figure 2 of Stubenrauch *et al.* (2010) and in Figure S1 of the supplement, contrasting distributions of the relative standard deviation of these cloud emissivities, $(\varepsilon(\lambda_i))/\varepsilon_{cld}$, of cloudy and clear sky scenes from CALIPSO samples. Guided by these figures and experimenting with thresholds to obtain a good agreement in cloud amount compared to CALIPSO-CloudSat (section 3) and to other datasets (section 4), we define the AIRS footprint as cloudy if the following conditions are fulfilled: $(\varepsilon(\lambda_i))/\varepsilon_{cld} < 0.17$ for ocean (both ancillary data), $(\varepsilon(\lambda_i))/\varepsilon_{cld} < 0.20$ for land (both ancillary data) and $(\varepsilon(\lambda_i))/\varepsilon_{cld} < 0.30 / 0.20$ for ice and snow (AIRS-NASA / ERA-Interim ancillary data).

For IASI we do not have the possibility to distinguish $(\varepsilon(\lambda_i))/\varepsilon_{cld}$ distributions according to CALIPSO-CloudSat cloudy and clear sky scenes. However, the overall distributions of $(\varepsilon(\lambda_i))/\varepsilon_{cld}$ are similar for AIRS and IASI, comparing retrievals based on ERA-Interim ancillary data. Therefore we use the same thresholds for the IASI cloud detection.

To reduce misidentification of clear sky as high-level clouds, only clouds with $\varepsilon_{cld} \times 0.10$ are considered.

2.5.4 Summary of changes compared to the previous version of the AIRS-LMD cloud retrieval

Compared to the retrieval used to produce the six-year AIRS-LMD cloud climatology (Stubenrauch *et al.*, 2010), the following changes have been implemented into the CIRS algorithm:

- extension of minimum cloud pressure from 106 hPa to 86 hPa,
- update of atmospheric and surface ancillary data from NASA V5 to NASA V6,
- improved interpolation of atmospheric and surface ancillary data,
- moving the cloud to the inversion level and scaling ε_{cld} in the case of atmospheric temperature inversions,
- improved radiative transfer computations of the TIGR atmospheric spectral transmissivities,
- adjusting the TIGR spectral transmissivity for the lowermost layer in accordance with the observed surface pressure,

- 1 • decreased cloud detection thresholds, due to improved radiative transfer computations,
- 2 • reducing the number of cloud detection tests to one, which is based on the coherence of cloud spectral
- 3 emissivity,
- 4 • considering clouds with $\varepsilon_{cl} \times 0.10$, instead of $\varepsilon_{cl} \times 0.05$,
- 5 • taking into account variable CO₂ concentration in spectral transmissivity estimates.

6 As we will see in section 4, the impact of these changes is in general small, but taking into account
7 variable CO₂ concentration is important for addressing the long-term variability of clouds.

8 **3 Evaluation of cloud properties using the A-Train synergy**

9 The lidar and radar of the CALIPSO and CloudSat missions, provide a unique opportunity to evaluate
10 the retrieved AIRS cloud properties such as cloud amount and cloud height, as well as to explore the
11 vertical structure of the AIRS cloud types (Stubenrauch *et al.*, 2010). These results can then be
12 transposed to cloud types determined by the CIRS retrieval using other IR sounders.

13 In the following, we analyse three years (2007-2009) of collocated AIRS-CALIPSO-CloudSat data,
14 separately for three latitude bands: tropical / subtropical latitudes (30°N-30°S), midlatitudes (30°N-60°N
15 and 30°S-60°S) and polar latitudes (60°N-90°N and 60°S-90°S).

16 **3.1 Cloud detection**

17 The hit rates (fraction of agreeing cloudy and clear cases) between the AIRS-CIRS cloud detection and
18 the lidar-radar cloud detection (section 2.4) are 85% (84%) over ocean, 82% (79%) over land and 70%
19 (73%) over ice / snow. Values in parantheses correspond to ERA-Interim ancillary data. Table 1 presents
20 separate comparisons for the three latitude bands. In general, the hit rates are quite high, considering that
21 CALIPSO and GEOPROF data only sample a small area of the AIRS footprints. They are slightly
22 higher over ocean than over land. Compared to the AIRS-LMD cloud retrieval presented in Stubenrauch
23 *et al.* (2010), the agreement with CALIPSO-CloudSat has improved both over ocean and land, but
24 slightly decreased over sea ice. The latter can be explained by applying now only one test over all surface
25 types. In the earlier version we used an additional brightness temperature difference test related to
26 temperature inversions. A detailed analysis (not shown) indicated that it also introduced noise.

27 To further illustrate CA uncertainties linked to ancillary data, we investigate, in Figure 2, geographical
28 maps of differences in CA and T_{surf} , using ancillary data from AIRS-NASA and from ERA-Interim.
29 With AIRS-NASA ancillary data, CA over land is often smaller during night and larger in the afternoon,
30 with T_{surf} also smaller during night and larger in the afternoon over large parts of the continents.
31 Considering the T_{surf} comparison with ARSA (section 2.5), this means that over land CA is slightly

1 underestimated during night with AIRS-NASA ancillary data, while slightly underestimated in the
 2 afternoon with ERA-Interim ancillary data. Patterns of differences in atmospheric water vapour are less
 3 reflected in those of CA (not shown), but slightly more atmospheric water vapour in the ancillary data (as
 4 in the tropics for AIRS-NASA compared to ARSA and ERA-Interim) might lead to a slight
 5 underestimation of CA.

6 **3.2 Cloud height**

7 Figure 3 presents normalized distributions of the difference between $z_{COD0.5}$ from CALIPSO (section 2.4)
 8 and z_{cld} , from AIRS for the three latitude bands. We compare results for $p_{cld} < 440$ hPa and $p_{cld} \times 440$
 9 hPa, separately for AIRS-NASA and ERA-Interim ancillary data. In general, all distributions peak
 10 around 0 km and are slightly narrower for lower level clouds than for high-level clouds. Results are
 11 similar for both ancillary data, with a slight cloud height overestimation of lower level clouds over
 12 tropical ocean for ERA-Interim (not shown), and a height overestimation of some clouds over polar
 13 ocean for AIRS-NASA ancillary data (not shown). The latter can be explained by the fact that in some of
 14 these regions T_{surf} and atmospheric profiles of good quality are only available in 10% of the time. When
 15 comparing distributions of $z_{top} - z_{cld}$, the peaks for lower clouds are still around 0 km, whereas for high-
 16 level clouds z_{cld} lies on average 1.5 km below the cloud top (not shown), very similar to results in
 17 Stubenrauch *et al.* (2010). This means that T_{cld} is about 10 K warmer than the cloud top (Figure S2 of the
 18 supplement). The broader distributions for high-level clouds compared to low-level clouds may be
 19 explained by the fact that high-level clouds often have diffuse cloud tops (e. g. Liao *et al.*, 1995),
 20 especially in the tropics ($z_{top} - z_{cld}$ is slightly larger for the same ϵ_{cld} , as shown in Figure 5). To summarize,
 21 z_{cld} can be approximated by i) the height of maximum lidar backscatter (Stubenrauch *et al.*, 2010), ii)
 22 $z_{COD0.5}$ (Figure 3), or iii) the mean layer height (for optically thin clouds) or the mean between cloud top
 23 and the height at which the cloud reaches opacity), as shown in Figure S2 (considering mid- p_{cld}).

24 For a more detailed investigation of the different height approximations, Figure 4 compares median
 25 values of $z_{cld} - z_{COD0.5}$, $z_{top} - z_{cld}$ and $(z_{top} - z_{cld}) / (z_{top} - z_{app\ base})$ as a function of ϵ_{cld} for high-level clouds. For
 26 this analysis we have selected cases for which z_{cld} lies between top and base of the closest GEOPROF
 27 cloud layer. This leaves about 82% / 73% / 57% of the statistics in tropics / midlatitudes / polar regions,
 28 respectively. z_{cld} varies from 1 km above for $\epsilon_{cld} = 0.1$ to 1 km below $z_{COD0.5}$ for $\epsilon_{cld} = 1$, assuming that
 29 $z_{COD0.5}$ is accurately estimated for all ϵ_{cld} (section 2.4). In that case, z_{cld} of thin cirrus should be
 30 approximated by a height with COD < 0.5 and z_{cld} of opaque high clouds by a height with COD > 0.5 .
 31 On the other hand, z_{cld} lies about 1 km to 2 km below z_{top} , the difference to cloud top increasing with ϵ_{cld}
 32 (except for ϵ_{cld} close to 1). Since $z_{top} - z_{app\ base}$ also increases with ϵ_{cld} , (not shown), $(z_{top} - z_{cld}) / (z_{top} - z_{app\ base})$

1 *base*) does not depend on ε_{cld} , and is about 0.5. We deduce that it probably needs less vertical extent for
2 opaque clouds than for semi-transparent cirrus to reach a COD of 0.5, while the χ^2 method determines a
3 height within the cloud, which corresponds well to the mean between cloud top and base or the height at
4 which the cloud reaches opacity, independent of ε_{cld} . This is important to take into account for the
5 determination of radiative fluxes and heating rates of upper tropospheric clouds, when using CIRS cloud
6 heights. We want to stress that also for low-level clouds $(z_{top} - z_{cld})/(z_{top} - z_{app\ base})$ is about 0.5 (0.4 to 0.6),
7 while z_{cld} lies only about 0.1 to 0.4 km below $z_{COD0.5}$, and about 0.5 km below z_{top} (Figure S3 of the
8 supplement).

9 Finally, Figure 5 presents normalized frequency distributions of z_{cld} , using both sets of ancillary data, and
10 of $z_{COD0.5}$, whenever clouds are detected (excluding subvisible cirrus, see section 2.4). The CALIPSO
11 $z_{COD0.5}$ distributions have a slightly larger part of high-level clouds, especially in the tropics, and the
12 AIRS z_{cld} distributions show a slightly larger part of low-level clouds over land. The latter disappear if
13 one considers only cases with all three CALIPSO samples cloudy within an AIRS golf ball. Thus these
14 low-level clouds are part of partly cloudy fields for which it is difficult to compare results from samples
15 of very different spatial resolution. The distributions compare better when only mostly covered cloud
16 fields are considered (three CALIPSO samples cloudy within an AIRS golf ball). In the tropics, the peak
17 of the AIRS z_{cld} distributions for high-level clouds is still slightly broader towards lower heights than for
18 CALIPSO (not shown). Additional filtering, excluding multi-layer clouds, ultimately leads to very
19 similar distributions, also presented in Figure 5. A plausible interpretation is, that in cases of multiple
20 cloud layers with the upper cloud layer not fully covering the large AIRS footprint, instrument received
21 radiation is mixed from different cloud layers, and thus z_{cld} is slightly lower than the one of the
22 uppermost cloud layer. The distributions in the midlatitudes still peak at slightly lower heights, because
23 high-level clouds in these latitudes are on average optically thicker (storm tracks) than in the tropics. In
24 these cases z_{cld} lies below $z_{COD0.5}$, as we have seen in Figure 4. The choice of ancillary data influences
25 only mildly the z_{cld} distributions, with a slightly larger contribution of low-level clouds over land for
26 ERA-Interim. This difference disappears if we consider only mostly covered cloud fields, as the
27 contribution of low-level clouds strongly decreases over land. Over ocean, the effect is much smaller.
28 This indicates that low-level clouds over ocean appear more often as stratus decks whereas those over
29 land appear more frequently as cumulus, as expected.

30 **4 Average cloud properties and variability**

31 In this section we give a short overview of cloud properties of the AIRS-CIRS and IASI-CIRS cloud
32 climatologies. Monthly L3 data, gridded at a spatial resolution of 1° latitude x 1° longitude, have been
33 produced in the same manner as for the GEWEX Cloud Assessment data base (Stubenrauch *et al.*,

1 2013): in a first step, cloud properties and their uncertainties, deduced from the χ^2 method, were
2 averaged per observation time over 1° latitude x 1° longitude, and in a second step, these were averaged
3 per month. In addition to the monthly averages, the data base also includes histograms of the cloud
4 properties.

5 Figure 6 compares normalized frequency distributions of p_{cld} (CP) over 30° wide latitude bands during
6 boreal winter and boreal summer, separately over land and over ocean. As one can see, the AIRS and
7 IASI CP distributions are very similar. Their relative contribution of high-level clouds is slightly larger
8 over land than over ocean, especially in the tropics, while the contribution of low-level clouds is larger
9 over ocean. Considering seasonality, the strongest signature is the shift of the Intertropical Convergence
10 Zone (ITCZ) towards the summer hemisphere, manifested by a large amount of high-level clouds (from
11 cirrus anvils), especially over land.

12 Figure 7 presents global averages of total cloud amount (CA) and relative contributions of high-level,
13 mid-level and low-level clouds, determined by dividing these cloud amounts (CAH, CAM, CAL) by
14 CA. The sum of the relative contributions, CAHR, CAMR and CALR is equal to 1. Relative cloud
15 amount values give an indication of how the detected clouds are vertically distributed in the atmosphere,
16 when observed from above. Global averages of AIRS-CIRS and IASI-CIRS are compared with those
17 from selected cloud climatologies of the GEWEX Cloud Assessment data base: the International
18 Satellite Cloud Climatology Project (ISCCP; Rossow and Schiffer, 1999), two cloud climatologies
19 derived from observations of the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the
20 Aqua satellite, by the MODIS Science Team (MODIS-ST; Frey *et al.*, 2008) and by the MODIS
21 CERES Science Team (MODIS-CE; Minnis *et al.*, 2011), and two cloud climatologies derived from
22 CALIPSO observations, the one of the CALIPSO Science Team (CALIPSO-ST; Winker *et al.*, 2009)
23 and the GCM-Oriented CALIPSO Cloud Products (CALIPSO-GOCCP; Chepfer *et al.*, 2010). The
24 latter two use vertical averaging (CALIPSO-GOCCP) and horizontal averaging (CALIPSO-ST) to
25 reduce the noise of the relatively small samples. The latter is more sensitive to thin layers of subvisible
26 cirrus. ISCCP is essentially using two atmospheric window channels (IR and VIS, the latter only during
27 daytime). Considering passive remote sensing, total cloud amount from the GEWEX Cloud Assessment
28 data base is about 0.68 ± 0.03 (Stubenrauch *et al.*, 2013), while CALIPSO-ST provides a cloud amount of
29 0.73, because it includes subvisible cirrus.

30 We separately examine daytime and nighttime observations. While all data sets agree quite well on CA,
31 with ISCCP and MODIS-CE providing smaller CA during night (both including VIS information for
32 cloud detection during daytime), CAHR exhibits a large spread, due to different sensitivity to thin cirrus :
33 active lidar is the most sensitive, followed by IR sounders. The CIRS results are very similar to the

1 results from the AIRS-LMD cloud climatology (Stubenrauch *et al.*, 2010). The choice of ancillary data
2 only slightly affects CA at night. IASI-CIRS and AIRS-CIRS results are also very similar, day and night.
3 They present global averages of CA around 0.67 \pm 0.70, formed by 40% high-level, 20% midlevel and
4 40% low-level uppermost clouds. This is in excellent agreement with the results from CALIPSO. The
5 slightly smaller value in CALIPSO CAMR (14% instead of 20%) is due to the different distinction
6 between high-level and mid-level clouds: CALIPSO uses cloud top height, whereas AIRS and IASI use
7 a cloud height which is about 1 km lower than the top (section 3.2). When combining VIS and IR
8 information, thin cirrus above low-level clouds tend to be misidentified as mid-level clouds (ISCCP) or
9 as low-level clouds (MODIS), leading to a not negligible underestimation of CAHR (30% instead of
10 40%). At night, when only the IR channel is available, ISCCP underestimates the height of all semi-
11 transparent high-level clouds, so that CAHR drops to 15%. When IR spectral information is available, as
12 for IR sounders and MODIS, results are similar to those during daytime.

13 Differences between ocean and land, also presented in Figure 7, correspond to about 0.15 in CA, with
14 about 20% more low-level clouds over ocean and about 10% more high-level and mid-level clouds over
15 land. The CIRS retrievals provide similar values during day and night. It is interesting to note that during
16 daytime the difference in CA shows a larger spread between the datasets, while at night the spread is
17 larger for CALR. At night, low-level clouds are more difficult to detect, especially over land.

18 Table 2 summarizes averages of these cloud amounts over the whole globe, over ocean and over land,
19 also contrasting NH and Southern hemisphere (SH) midlatitudes (30°-60°) and tropics (15°N-15°S). The
20 largest fraction of high-level clouds is situated in the tropics, while the largest fraction of single layer
21 low-level clouds is in the SH midlatitudes. Only about 10% of all clouds in the tropics are single layer
22 midlevel clouds, compared to about 22% in the midlatitudes. As already discussed in sections 2.5 and
23 3.1, the uncertainty due to ancillary data in CA, as well as in CALR, is largest over land (about 5% and
24 10%, respectively), because low-level clouds are underestimated with AIRS-NASA during night and
25 with ERA-Interim in the afternoon. Uncertainties are much smaller for high-level clouds. Considering
26 further three distinct high-level cloud classes, opaque, thick cirrus and thin cirrus (section 2.5), high-level
27 opaque clouds only represent about 5.2% of all clouds, while relative cloud amounts of thick cirrus and
28 thin cirrus are about 21.5% and 13%. Maximum values are observed in the tropics, of 7.5%, 27.5% and
29 21.5%, respectively (Table 3). The independent use of p_{cld} and ε_{cld} enabled us to build a climatology of
30 upper tropospheric cloud systems, using ε_{cld} to distinguish convective core, cirrus anvil and thin cirrus of
31 these systems. These data have revealed for the first time that the ε_{cld} structure of tropical anvils is related
32 to the convective depth (Protopapadaki *et al.*, 2017).

1 Figure 8 presents zonal averages of CA, CAH and CAL as well as effective cloud amount for total
2 (CAE) high-level (CAEH) and low-level (CAEL) clouds, for the three CIRS climatologies (AIRS, using
3 two sets of ancillary data, and IASI) and the prior AIRS-LMD cloud climatology. Effective cloud
4 amount corresponds to the cloud amount weighted by cloud emissivity. It therefore includes the IR
5 radiative effect of the detected clouds. In general, CAE is about 0.2 smaller than CA. Maximum CAH
6 and CAEH appear in the ITCZ, while maximum CAL and CAEL is found in the SH midlatitudes. The
7 results of all CIRS climatologies are very similar, with AIRS-CIRS using AIRS-NASA ancillary data
8 presenting slightly more high-level clouds and less low-level clouds around 60S and slightly less CA and
9 CAL in the NH polar region.

10 Figure 9 presents geographical maps of annual CAH and CAL. We compare AIRS-CIRS, ISCCP and
11 CALIPSO-GOCCP, the latter two from the GEWEX Cloud Assessment data base. In all datasets the
12 most prominent feature in CAH is the ITCZ. However, due to the better sensitivity to cirrus, the absolute
13 values are more pronounced for AIRS-CIRS (IASI-CIRS, not shown) and CALIPSO-GOCCP than for
14 ISCCP. Due to the narrow nadir track of CALIPSO and the reduced statistics of CALIPSO-GOCCP in
15 the present GEWEX Cloud Assessment data base, these data look noisier than AIRS-CIRS and ISCCP.
16 Considering CAL, AIRS-CIRS captures well the stratocumulus regions off the West coasts of the
17 continents and stratus decks in the subtropical subsidence regions in winter, even if this type of cloud is
18 easier to detect by using instruments including VIS channels (during daytime, ISCCP) or active
19 instruments (CALIPSO-GOCCP).

20 Time series of deseasonalized anomalies in global monthly mean CA, CAEH and CAEL of the three
21 CIRS data sets are shown in Figure 10 over the time period of 2004 ó 2016 for AIRS and 2008 ó 2016
22 for IASI. To illustrate the effect of the calibration accounting for changes in atmospheric CO₂
23 concentration (section 2.5.2), the time series of the AIRS-CIRS CA anomalies, without this correction, is
24 added. Whereas the uncorrected CA anomalies increase by about 0.040 within a decade, the magnitude
25 of the calibrated CA and CAEL variations lie within 0.010 and of CAEH within 0.005, being mostly
26 stable within the uncertainty range.

27 Latitudinal seasonal cycles of CA, CAH, CAL and T_{cld} (CT) from the different data sets agree in general
28 quite well (Figure S4 of the supplement). The most prominent features of the latitudinal seasonal cycles
29 are i) the shift of the ITCZ towards the summer hemisphere, seen as an amplitudinal signal of 0.1 in CA,
30 0.3 in CAH and 16 K in CT in the SH and NH tropical bands (mostly over land, not shown) and ii) less
31 clouds in late summer in the midlatitudes (mostly over ocean and stronger in NH, not shown). The
32 seasonal cycle of CT is largest in the polar regions (coherent for all data sets) and smallest in SH
33 midlatitudes, with amplitudes ranging from 20 K to 10 K. However, while the CT amplitude is linked to

1 change in cloud height at low latitudes, it is more related to change in atmospheric temperature (and
2 corresponding CT) at higher latitudes.

3 **5 Applications**

4 After having demonstrated the reliability of the CIRS cloud climatologies in sections 3 and 4, we present
5 analyses on upper tropospheric (UT) cloud variability with respect to changes in atmospheric conditions.
6 These illustrate the added value of the CIRS cloud data for climate studies.

7 **5.1 Hemispheric differences in UT clouds**

8 While the NH and the SH reflect the same amount of sunlight within 0.2 Wm^{-2} (Stephens *et al.*, 2015),
9 there is a small energy imbalance between both hemispheres of our planet, with slightly more energy
10 absorbed by the SH (0.9 Wm^{-2}). This yields more frequent precipitation in the SH while more intense
11 precipitation in the NH (Stephens *et al.*, 2016). The latter might be linked to the characteristics of the
12 ITCZ, a zone of strong convection, which itself produces large cirrus anvils. As the size of these anvils is
13 on average positively related to convective strength (e. g. Protopapadaki *et al.*, 2017), we explore the
14 annual mean and seasonal hemispheric difference of high cloud amount and try to relate it to the
15 characteristics of the ITCZ, such as its peak strength, the latitudinal position of the peak and its width.

16 The ITCZ characteristics have been determined by fitting a Gaussian around the tropical peak of the
17 latitudinal CAH distributions (Figure 8), per month and year. This yields the latitude of the peak position,
18 the value of the peak itself, and the width of the tropical CAH distribution. From Figure 11 we deduce
19 that the annual NH-SH difference in CAH is 0.05, with a pronounced seasonal cycle of about 0.3 in
20 amplitude. Results from the three CIRS cloud climatologies (AIRS with two ancillary data sets and
21 IASI), AIRS-LMD, CALIPSO-GOCCP, ISCCP and MODIS-CE are similar. This seasonal cycle is
22 well related to the one of the ITCZ peak latitude, which moves up to 12°N in July. It is interesting to note
23 that the width of the ITCZ is smaller in July / August (10.5° ó 12.5°) than in January (17°) and the CAH
24 peak is about 10% larger in August than in January. This might suggest a more intense ITCZ (and hence
25 more intense precipitation) when it is located in the NH than when it is located in the SH.

26 All datasets agree well on the ITCZ peak latitude. The smaller maximum CAH values of MODIS-CE
27 and ISCCP are due to smaller sensitivity to thin cirrus, and the reduced seasonal cycle of maximum
28 CAH and of ITCZ width for CALIPSO-GOCCP is due to the inclusion of ubiquitous thinner cirrus,
29 leading to less well pronounced CAH minima in the subtropics. The CIRS climatologies reveal the
30 seasonal behaviour of the ITCZ characteristics clearly. Figure 11 confirms and extends the interpretation
31 of the results of (Stephens *et al.*, 2016), by displaying a relation between the hemispheric difference of

1 CAH and characteristics of the ITCZ, which seems to be more intense when its peak is situated in the
2 NH (smaller width and larger maximum).

3 **5.2 Relating surface temperature anomalies to changes in UT clouds**

4 Since the observational period of AIRS and IASI is too short to directly study long-term cloud variability
5 related to climate warming, an alternative approach is to analyse cloud variability in response to
6 interannual climate variability. Though interannual global mean surface temperature anomalies might
7 not directly relate to patterns of anthropogenic climate warming, Zhou *et al.* (2015) have shown that
8 interannual cloud feedback may be used to directly constrain the long-term cloud feedback. Changes in
9 tropical UT clouds leads to variations in atmospheric heating and cooling which then may influence the
10 large-scale circulation, as has already been shown by Slingo and Slingo (1991).

11 Since the radiative effects of high opaque clouds and thin cirrus are quite different, we investigate the
12 geographical patterns of UT cloud amount anomalies with respect to tropical and global mean surface
13 temperature anomalies, by separating them into opaque, cirrus and thin cirrus ($\varepsilon_{cld} > 0.95$, $0.4 - 0.95$ and
14 < 0.4 , corresponding to visible COD > 6 , $1 - 6$ and < 1 , respectively). By making use of the whole
15 period between 2003 and 2015 (covering 156 months), we estimate a change in UT cloud amount as a
16 function of change in mean surface temperature by a linear regression of their deseasonalized monthly
17 anomalies, at a spatial resolution of 1° latitude x 1° longitude. Similar techniques were already utilised in
18 other studies related to El Niño ó Southern Oscillation (ENSO) and cloud feedback (e.g. Lloyd *et al.*,
19 2012; Zhou *et al.*, 2013, Liu *et al.*, 2017). Figure 12 presents the change in amount of high opaque cloud
20 (mostly of convective origin), in thick cirrus (often formed from convective outflow as anvils) and in thin
21 cirrus (which might be formed as anvil or via in situ freezing) per K of global surface warming, obtained
22 as the linear slopes of these deseasonalized monthly anomaly relationships. The cloud amounts are from
23 AIRS-CIRS, while the surface temperatures are from the ERA-Interim ancillary data. Results are very
24 similar when using T_{surf} anomalies from AIRS-NASA (not shown). Zhou *et al.* (2013) have shown that
25 ERA-Interim T_{surf} anomalies give similar results in their short-term cloud feedback analysis, compared to
26 other T_{surf} data sets. In our study, we concentrate on the change of UT clouds of different height ($p_{cld} <$
27 440 hPa and $p_{cld} < 330$ hPa), and we compare changes in absolute UT cloud amounts and in UT cloud
28 amounts relative to total cloud amount. The geographical patterns of the relative slope uncertainty are
29 shown in Figure S5 in the supplement. In general, large changes in cloud amount per K of warming have
30 smaller uncertainty than small ones, indicating robust patterns.

31 During this period, global mean T_{surf} anomalies and tropical mean T_{surf} anomalies are strongly correlated
32 (not shown), and the spatial patterns in Figure 12 are compatible with ENSO-like patterns. The left

1 panels of Figure 12 agree quite well with Figure 8 of Liu *et al.* (2017), based on MODIS cloud amount
2 and HadCRUT4 T_{surf} anomalies, even though our cloud types categories differ slightly. In particular, we
3 have separated thin cirrus. Therefore the analyses suggest that the change patterns address ENSO
4 variability rather than long-term trends. When considering relative cloud type changes (middle panels in
5 Figure 12), the signals are stronger. An interesting feature appears when considering changes in the
6 relative amounts of higher clouds ($p_{cld} < 330$ hPa, left panels of Figure 12): While the high opaque
7 clouds, linked to strong precipitation (Protopapadaki *et al.*, 2017), relative to all clouds, increase in a
8 narrow band in the tropics, there is a large increase in relative thin cirrus amount around these regions,
9 the latter might directly affect the atmospheric circulation through their radiative heating (e.g. Sohn,
10 1999; Lebsock *et al.*, 2010).

11 As in Liu *et al.* (2017), we have also examined linear regression slopes from anomaly averages over the
12 tropics and other latitudinal bands. Although in general the relationships are very noisy, on the
13 interannual scale tropical cirrus amount slightly decreases with warming (-0.76 ± 0.21 %/K), while thin
14 cirrus amount seems not affected (-0.09 ± 0.20 %/K), in agreement with Liu *et al.* (2017). However,
15 when considering changes in tropical cirrus and thin cirrus amount relative to total cloud amount, at
16 higher altitude ($p_{cld} < 330$ hPa), both increase with warming (1.87 ± 0.52 %/K and 1.70 ± 0.54 %/K),
17 which means that these clouds are more frequent among all clouds when T_{surf} gets warmer.

18 Even though the changes in mean T_{surf} are mostly linked to interannual variability over the studied period
19 and it is still uncertain how to relate these to long-term patterns due to anthropogenic climate warming, it
20 is very interesting to note that changes in amounts of high opaque clouds and thin cirrus, relative to all
21 clouds, show very different geographical patterns. To get a better understanding on the underlying
22 feedback processes one has to consider the heating rates of these UT cloud systems and link them to the
23 dynamics, which is foreseen in future work.

24 **6 Conclusions**

25 We have presented two global climatologies of cloud properties, built from AIRS and IASI observations
26 by the CIRS cloud retrieval. This retrieval software package, developed at LMD, can be easily adapted
27 to any IR sounder. The retrieval method itself, based on a weighted χ^2 method on radiances along the
28 wing of the $15 \mu\text{m}$ CO_2 absorption band, and a multi-spectral a posteriori cloud detection, based on the
29 spectral coherence of retrieved cloud emissivities, have been evaluated in previous publications. In this
30 study, we have further demonstrated the reliability of these updated cloud climatologies. IR sounders are
31 especially advantageous to retrieve upper tropospheric cloud properties, as they reliably determine cirrus
32 properties down to an IR optical depth of 0.1, day and night. The CIRS retrieval uses improved radiative

1 transfer modelling, employs the latest ancillary data (surface temperature, atmospheric profiles), and
2 accounts for atmospheric spectral transmissivity changes associated with latitudinal, seasonal and
3 interannual atmospheric CO₂ concentration variations. The latter eliminates an artificial CA trend of
4 about 4% over the observation period 2004 to 2016: The magnitude of cloud amount and effective low-
5 level cloud amount deseasonalized variations lie within 1% and of effective high-level cloud amount
6 within 0.5% over this period.

7 Ancillary data from the meteorological reanalyses ERA-Interim have been interpolated to the
8 observation times of AIRS and IASI. Additional ancillary data, established from NASA AIRS retrievals,
9 permitted to iteratively make adjustments to both sets of ancillary data for optimal results in cloud
10 properties and to estimate uncertainties in cloud amounts. Since the cloud detection depends on the
11 coherence of spectral cloud emissivity, the surface temperature influences only slightly the cloud amount
12 (in particular the one of low-level clouds). AIRS total cloud amount is 70% (67%), high-level cloud
13 amount 27% (27%) and low-level cloud amount 29% (27%), using ERA-Interim (AIRS-NASA)
14 ancillary data. This corresponds to uncertainty estimates of 5% and 10% on global averages of CA and
15 CAL, respectively. Uncertainties are larger over land and ice or snow than over ocean, in particular
16 because T_{surf} of ERA-Interim is underestimated in the afternoon and T_{surf} of AIRS-NASA is
17 underestimated during night due to cloud contamination. In the future, the CIRS cloud retrieval might
18 use ancillary data from the new ECMWF meteorological reanalysis ERA5, with a better temporal and
19 spatial resolution.

20 Cloud detection hit rates between AIRS-CIRS and CALIPSO-CloudSat are 84% (85%) over ocean,
21 82% (79%) over land and 70% (73%) over ice and snow, for ERA-Interim (AIRS-NASA) ancillary
22 data. Typical p_{cld} uncertainties range from 30 hPa for high-level clouds to 120 hPa for low-level clouds,
23 which corresponds to about 1.2 km. A comparison with CALIPSO-CloudSat shows, that on average the
24 CIRS retrieved cloud height is close to cloud top in the case of low-level clouds and lies about 1 km
25 below cloud top in the case of high-level clouds. The latter leads to retrieved cloud temperatures which
26 are about 10 K warmer than the cloud top. This has to be considered when determining radiative effects
27 or when evaluating climate models. The CIRS retrieved cloud height can be approximated by the mean
28 layer height (for optically thin clouds) or the mean between cloud top and the height at which the cloud
29 reaches opacity, for both high-level and low-level clouds. While for low-level clouds this vertical
30 distance is about 0.5 km, for high-level clouds it slightly increases with ε_{cld} , from 0.7 km to 1.5 km, with
31 slightly larger values in the tropics than in the midlatitudes, linked to diffusive cloud tops.

32 Total cloud amount is partitioned into about 40% high-level clouds, 40% low-level clouds and 20% mid-
33 level clouds. The latter two categories are only detected in the absence of upper clouds. Upper

1 tropospheric clouds are most abundant in the tropics, where high opaque clouds make out 7.5%, thick
2 cirrus 27.5% and thin cirrus 21.5% of all clouds. IASI values are very similar. The most prominent
3 feature of latitudinal seasonal cycles is the shift of the ITCZ towards the summer hemisphere, seen as an
4 amplitudinal signal of 0.1 in CA, 0.3 in CAH and 16 K in CT in the SH and NH tropical bands (and
5 even stronger over land).

6 The 5% annual mean excess in upper tropospheric cloud amount in the Northern compared to the
7 Southern hemisphere has a pronounced seasonal cycle with a maximum of 25% in boreal summer have
8 been related to the characteristics of the ITCZ. The annual mean ITCZ peak latitude lies about 5°N with
9 a maximum of 10°N in boreal summer. At that time the ITCZ width is also narrower and the peak
10 slightly larger. This suggests that the NH-SH excess in CAH is mostly determined by the position of the
11 ITCZ.

12 To illustrate the added value of the CIRS cloud data for climate studies, we have finally presented
13 geographical patterns in changes of amount of high opaque, cirrus and thin cirrus with respect to global
14 mean T_{surf} changes. These are in agreement with earlier studies, while an examination of changes in
15 tropical high cirrus and thin cirrus amounts relative to total cloud amount revealed that these are more
16 frequent among all clouds when T_{surf} gets warmer. Even though the change in mean T_{surf} is mostly
17 linked to ENSO variability over the studied period and it is still uncertain how to relate these to long-term
18 patterns due to anthropogenic climate warming, the large difference in geographical patterns in changes
19 of amounts of high opaque clouds and thin cirrus, relative to total cloud amount, indicates that their
20 response to climate change may be different. This might then have consequences on the
21 atmospheric circulation. To get a better understanding on the underlying feedback processes, one has
22 to consider the heating rates of these upper tropospheric cloud systems and link them to the dynamics.
23 Therefore the AIRS-CIRS and IASI-CIRS cloud data have been further used to build upper tropospheric
24 cloud systems (based on p_{cld}) and then to distinguish convective cores, cirrus anvil and thin cirrus
25 according to ε_{cld} (Protopapadaki *et al.*, 2017). These data are being further exploited, together with other
26 data and modelling at different scales, within the framework of the GEWEX PROcess Evaluation Study
27 on Upper Tropospheric Clouds and Convection (UTCC PROES, Stubenrauch and Stephens, 2017) to
28 advance our understanding on UT cloud feedbacks.

29 The AIRS-CIRS and IASI-CIRS cloud climatologies will be made available at the French data centre
30 AERIS, which also will continue their production.

31

1 **7 Data availability**

2 AIRS L1 data are available at <https://mirador.gsfc.nasa.gov/>. The NASA Science Team L2 standard
3 products (Version 6; Olsen *et al.*, 2017) are available at <https://mirador.gsfc.nasa.gov/>. IASI L1 data are
4 available at the French Data Centre AEROS. IASI L2 data provided by NOAA, are available at the
5 Comprehensive Large Array-data Stewardship System (CLASS) center ([https://www.
6 class.ncdc.noaa.gov](https://www.class.ncdc.noaa.gov)). The ARSA database is available at : [http://climserv.ipsl.polytechnique.fr/fr/les-
8 donnees/arsa-analyzed-radiosoundingsarchive.html](http://climserv.ipsl.polytechnique.fr/fr/les-
7 donnees/arsa-analyzed-radiosoundingsarchive.html). The operational version of the 4A radiative transfer
9 model (Scott and Chédin, 1981) is available at <http://www.4aop.noveltis.com>. The cloud climatologies
10 of the GEWEX Cloud Assessment data base are available at: <http://ipsl.polytechnique.fr/gewexca>. The
11 AIRS-CIRS and IASI-CIRS cloud climatologies will be made available by the French Data Centre
AERIS.

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1 Table 1. Hit rates between AIRS-CIRS and CALIPSO-CloudSat cloud detection. Statistics include three
 2 years (2007-2009) collocated observations at 1:30AM LT.

surface \ latitude	tropics		mid- latitudes		polar	
ancillary data	AIRS	ERA	AIRS	ERA	AIRS	ERA
ocean	86.5%	84.2%	90.2%	91.5%	93.0%	95.0%
land	86.4%	83.2%	80.7%	77.6%	77.3%	79.7%
sea ice			71.5%	82.0%	71.2%	81.2%
snow	73.5%	71.9%	74.9%	68.5%	65.5%	66.7%

3
 4 Table 2. Averages of CA, CAHR, CAMR and CALR (in %) from AIRS-LMD (2003-2009) / AIRS-
 5 CIRS (2003-2015, with AIRS-NASA / ERA-Interim ancillary data) / IASI-CIRS (2008-2015, with
 6 ERA-Interim ancillary data).

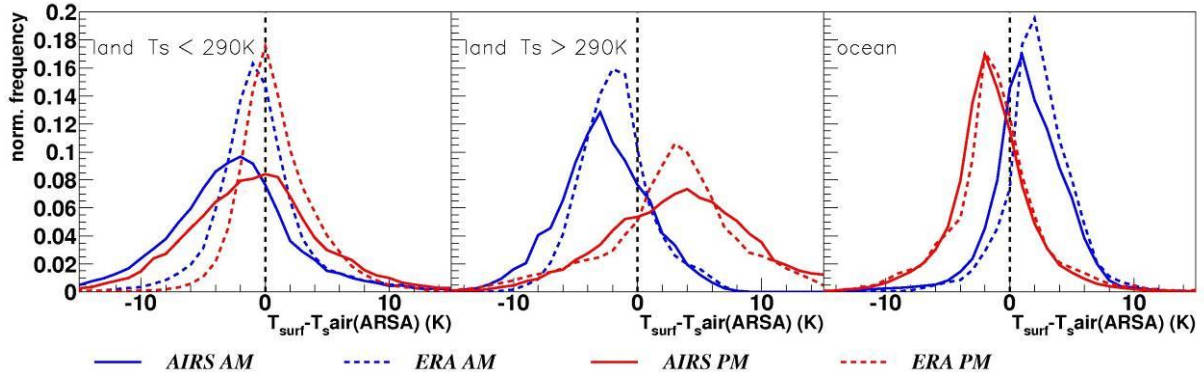
latitude band	CA (%)	CAHR (%)	CAMR (%)	CALR (%)
globe	67 / 67 / 70 / 67	41 / 41 / 40 / 40	18 / 19 / 19 / 20	41 / 40 / 41 / 40
ocean	72 / 71 / 74 / 72	38 / 38 / 37 / 37	16 / 16 / 17 / 18	47 / 45 / 46 / 44
land	56 / 57 / 59 / 56	48 / 49 / 47 / 47	23 / 25 / 23 / 23	29 / 27 / 30 / 30
60°N ó 30°N	69 / 69 / 72 / 69	40 / 40 / 40 / 40	22 / 23 / 22 / 22	38 / 37 / 38 / 38
15°N ó 15°S	67 / 63 / 66 / 62	59 / 58 / 57 / 58	11 / 10 / 10 / 11	30 / 32 / 33 / 31
30°S ó 60°S	80 / 84 / 85 / 85	28 / 30 / 30 / 29	21 / 23 / 22 / 23	51 / 47 / 48 / 48

10
 11 Table 3. Averages of relative amount (in %) of opaque ($\epsilon_{\text{cld}} > 0.95$), cirrus ($0.95 > \epsilon_{\text{cld}} > 0.5$) and thin
 12 cirrus ($0.5 > \epsilon_{\text{cld}} > 0.1$) from AIRS-CIRS (2003-2015, using AIRS-NASA / ERA-Interim ancillary data)
 13 / IASI-CIRS (2008-2015, using ERA-Interim ancillary data).

latitude band	opaque / tot CA	cirrus / tot CA	thin Cirrus / tot CA
globe	5.3 / 5.0 / 5.4	21.7 / 21.5 / 20.9	13.4 / 13.0 / 12.9
ocean	5.0 / 4.5 / 4.9	20.0 / 19.9 / 19.2	12.5 / 12.0 / 12.1
land	6.1 / 5.9 / 6.6	25.8 / 25.3 / 24.9	15.6 / 15.2 / 14.7
60°N ó 30°N	5.4 / 4.8 / 5.4	22.9 / 23.5 / 22.8	11.1 / 11.0 / 10.9
15°N ó 15°S	7.3 / 7.0 / 7.7	28.2 / 27.5 / 26.8	21.6 / 21.3 / 22.1
30°S ó 60°S	4.8 / 4.2 / 4.4	17.5 / 18.9 / 18.1	6.9 / 6.6 / 5.9

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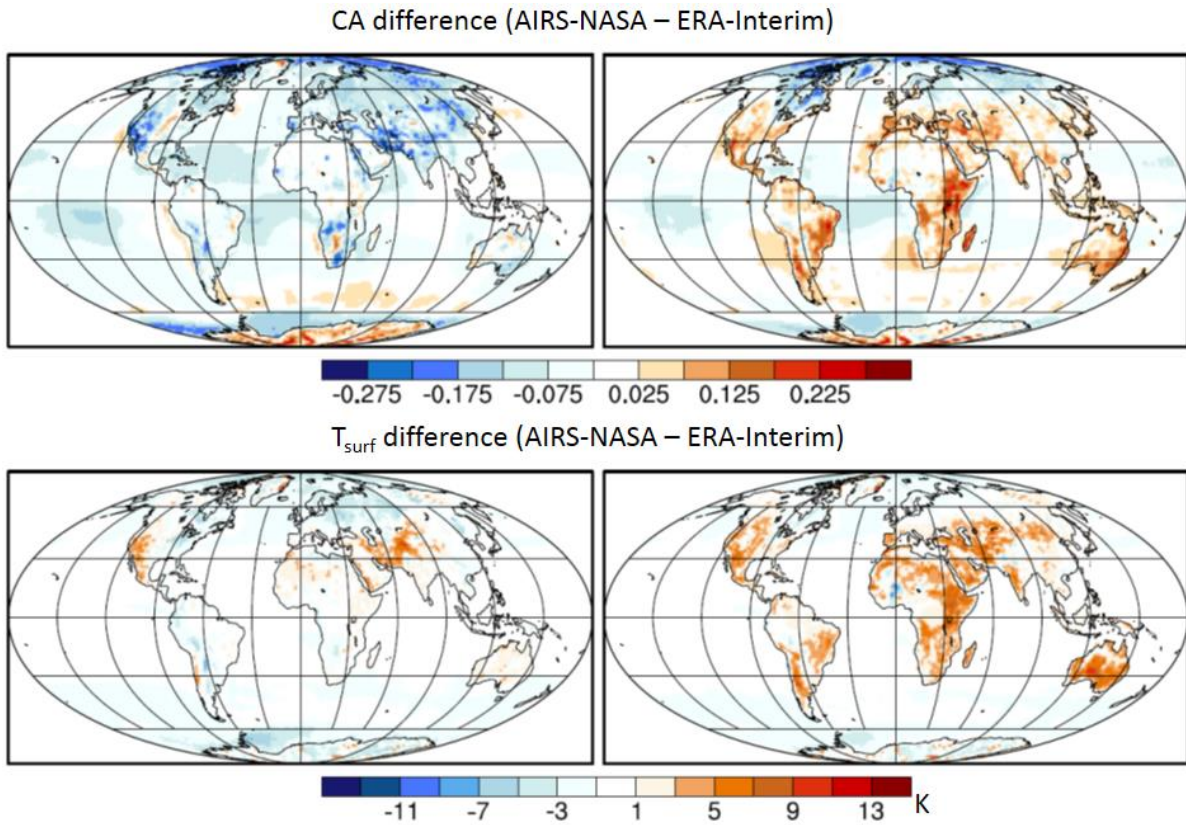
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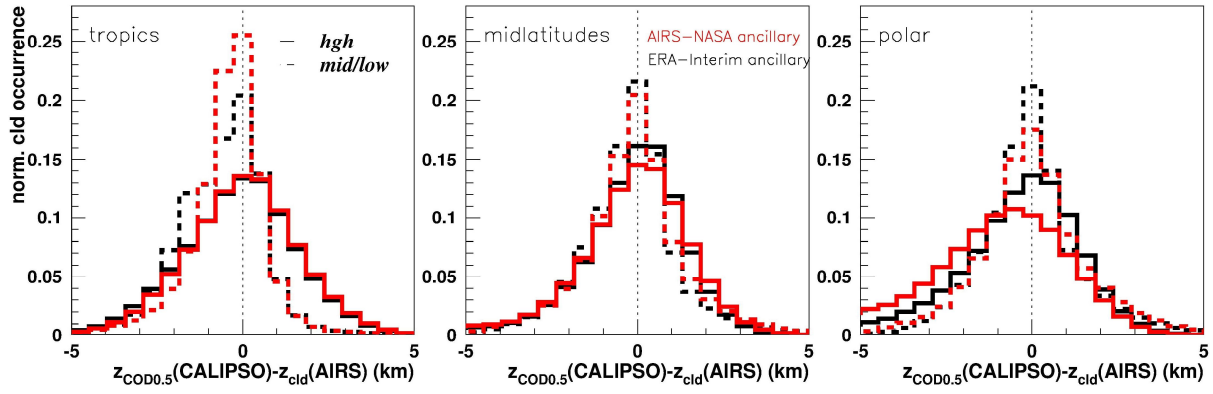
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3 Figure 1. Normalized distributions of the difference between surface skin temperature, as used in the
4 cloud retrieval, deduced from AIRS-NASA of good quality and from ERA-Interim, and collocated
5 surface air temperature of the ARSA data base. Statistics includes January and July from 2003 ó 2015,
6 separately over land for colder temperatures ($T_{surf} < 290$ K), over land for warmer temperatures ($T_{surf} >$
7 290 K) and over ocean.

8



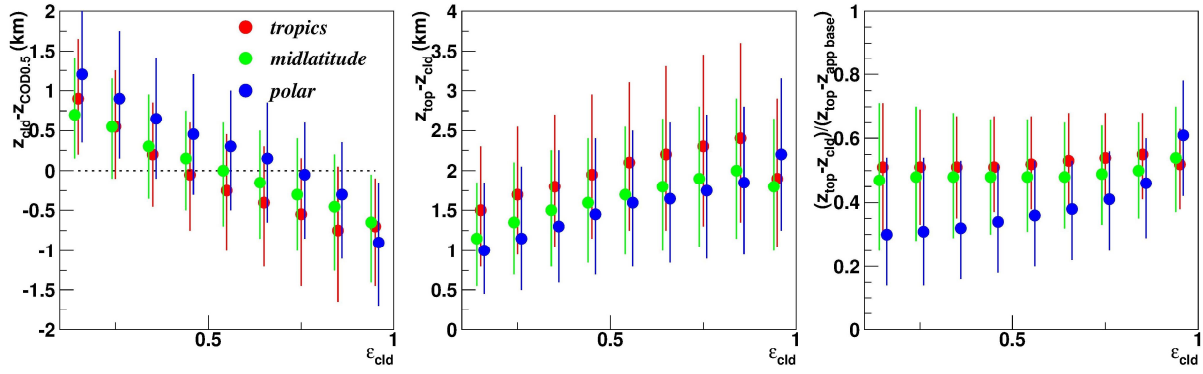
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 2 Figure 2. Geographical maps of difference in total CA (above) between the two AIRS-CIRS data sets,
 3 based on ancillary data from AIRS-NASA and from ERA-Interim, and in T_{surf} (below) between AIRS-
 4 NASA and ERA-Interim as used in the retrieval, separately at 1:30AM (left) and at 1:30PM (right)
 5



1

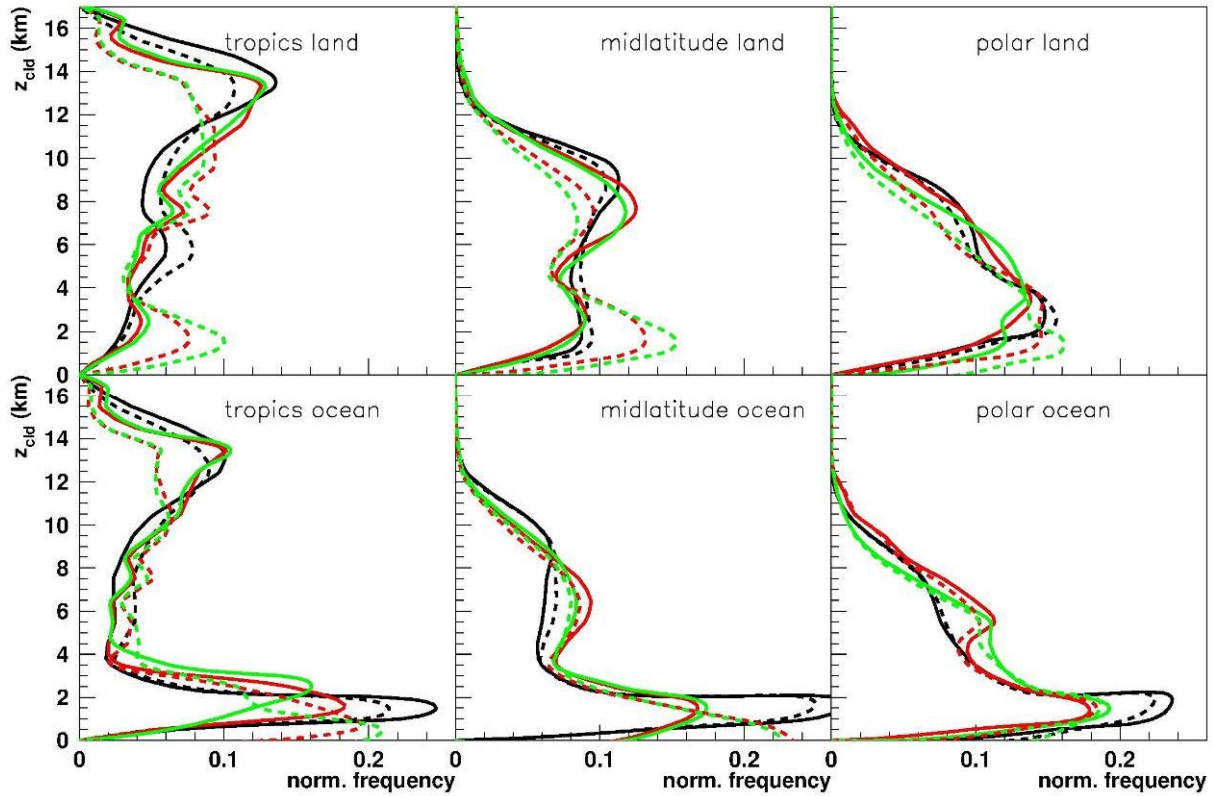
2 Figure 3. Normalized frequency distributions of the difference between the cloud height at which the
 3 optical depth reaches a value of 0.5 from CALIPSO and z_{cld} from AIRS; z_{cld} is compared to the cloud
 4 layer of CALIPSO, which corresponds to the one of CloudSat-lidar GEOPROF, and which is the closest
 5 to z_{cld} . Analysis over tropics (30°N-30°S), midlatitudes (30°-60°) and polar latitudes (60°-85°), separately
 6 for high-level clouds and for clouds with $p_{cld} > 440$ hPa. The effect of using different ancillary data is
 7 also presented. Statistics includes three years (2007-2009) of observations at 1:30AM LT.

8

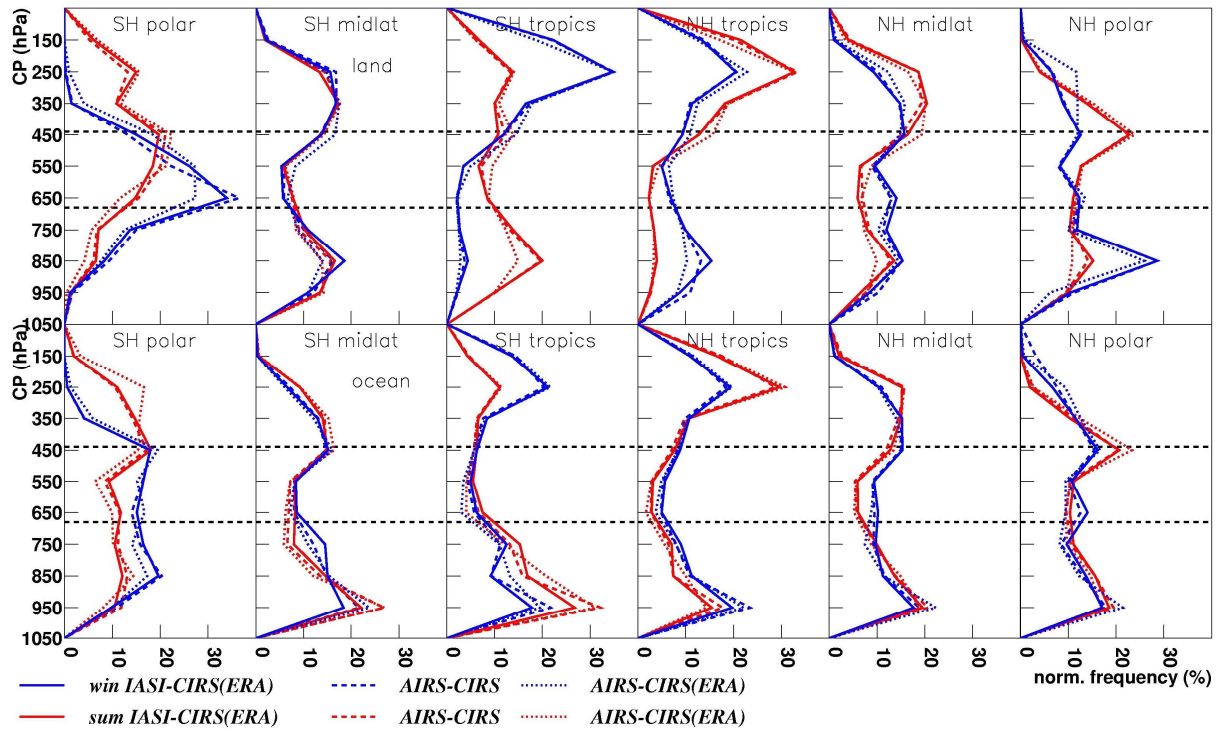


1
 2 Figure 4. a) $z_{cld} - z_{COD0.5}$, b) $z_{top} - z_{cld}$ and c) $(z_{top} - z_{cld}) / (z_{top} - z_{app\ base})$, as function of ϵ_{cld} for high-level
 3 clouds in the tropics, midlatitudes and polar latitudes. Presented are median values and the interquartile
 4 ranges. Three years of statistics, for which z_{cld} and $z_{COD0.5}$ lie within vertical cloud borders from
 5 GEOPROF. Observations at 1:30AMLT.

6

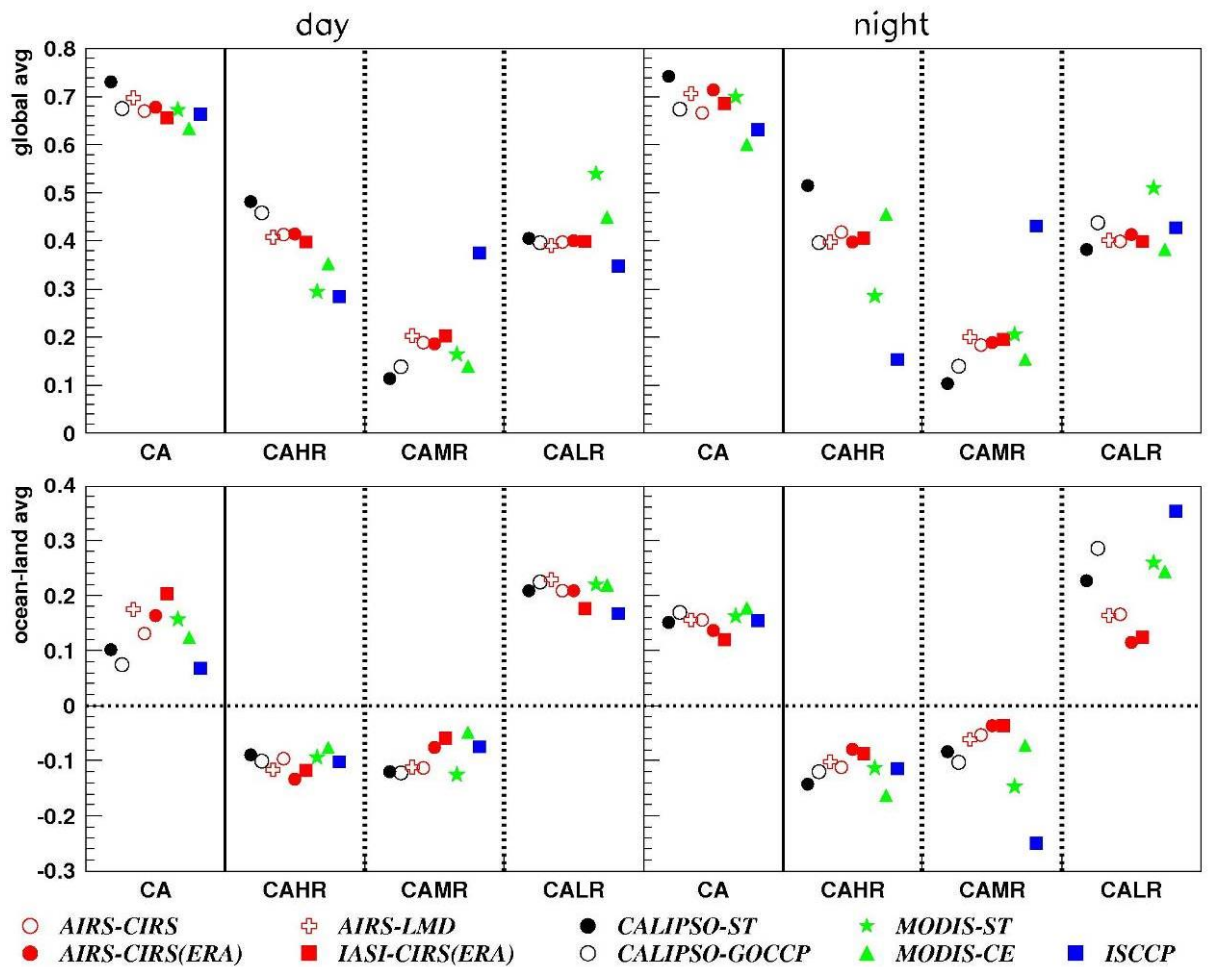


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 2 Figure 5. Normalized frequency distributions of $z_{COD0.5}$ from CALIPSO (black) and of z_{cld} from AIRS,
 3 using ancillary data from AIRS-NASA (red) and from ERA-Interim (green), separately over land (top)
 4 and over ocean (bottom), in the tropics, midlatitudes and polar latitudes. For each data set, two
 5 distributions are compared: statistics of all detected clouds, except subvisible cirrus, (dashed line) and
 6 only of single layer clouds with a cloud coverage filling the AIRS golf ball (full line).



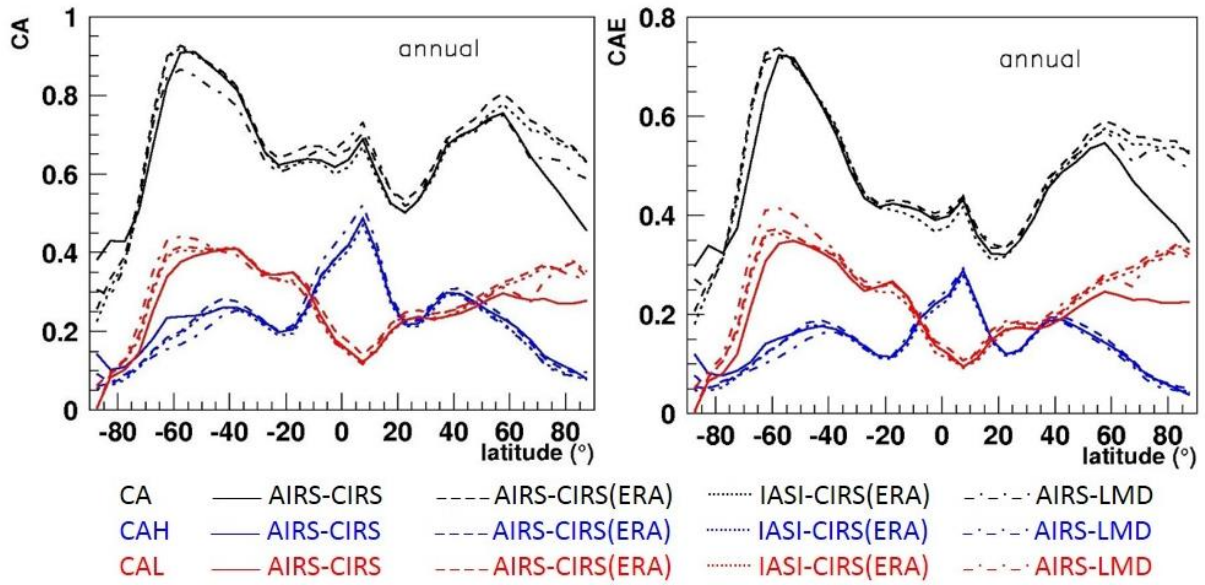
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2 Figure 6. Normalized frequency distributions of p_{cld} , separately over land and over ocean in six latitude
 3 bands of 30° from SH polar (left) to NH polar latitudes (right), in boreal winter (December, January,
 4 February; blue) and in boreal summer (June, July, August; red). Compared are results from AIRS-CIRS
 5 using two sets of ancillary data (AIRS-NASA, dashed line) and (ERA-Interim, dotted line), as well as
 6 from IASI-CIRS (full line), Statistics from 2008.



1
2 Figure 7. Top: Global averages of total cloud amount (CA) and fraction of high-level, mid-level and
3 low-level cloud amount, relative to total cloud amount, (CAHR + CAMR + CALR = 1). Comparisons
4 of IR sounder cloud data (AIRS, IASI) with L3 data from the GEWEX Cloud Assessment data base,
5 separately for observations mostly during day (1:30PM; 3:00PM for ISCCP and 9:30AM for IASI, left),
6 and mostly during night (1:30AM; 3:00AM for ISCCP and 9:30PM for IASI). Compared to the original
7 ISCCP data, the day-night adjustment on CA has not been included to better illustrate the differences
8 between VIS-IR and IR-only results. Bottom: Averages of ocean-land differences for the same
9 parameters and data sets.

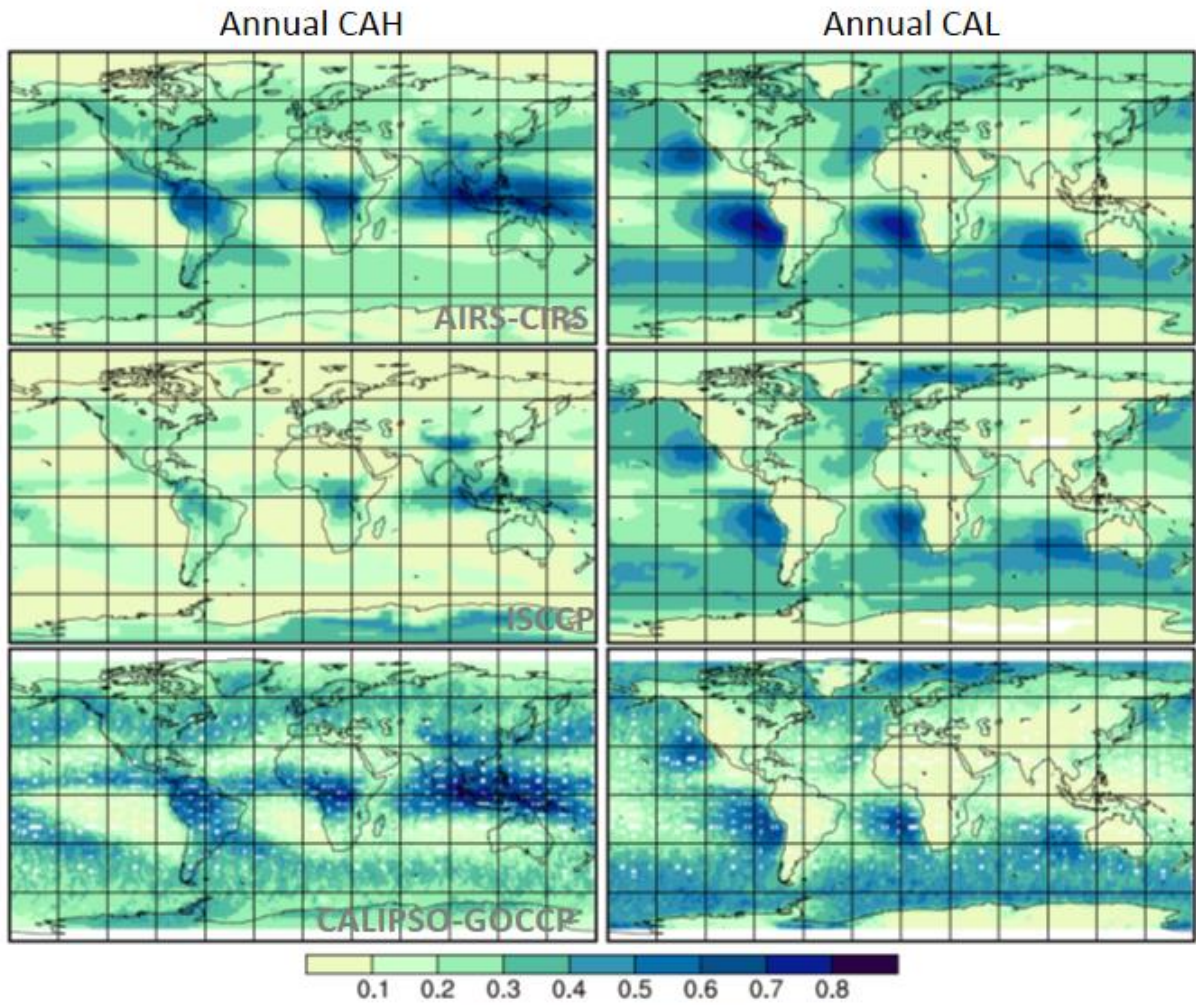
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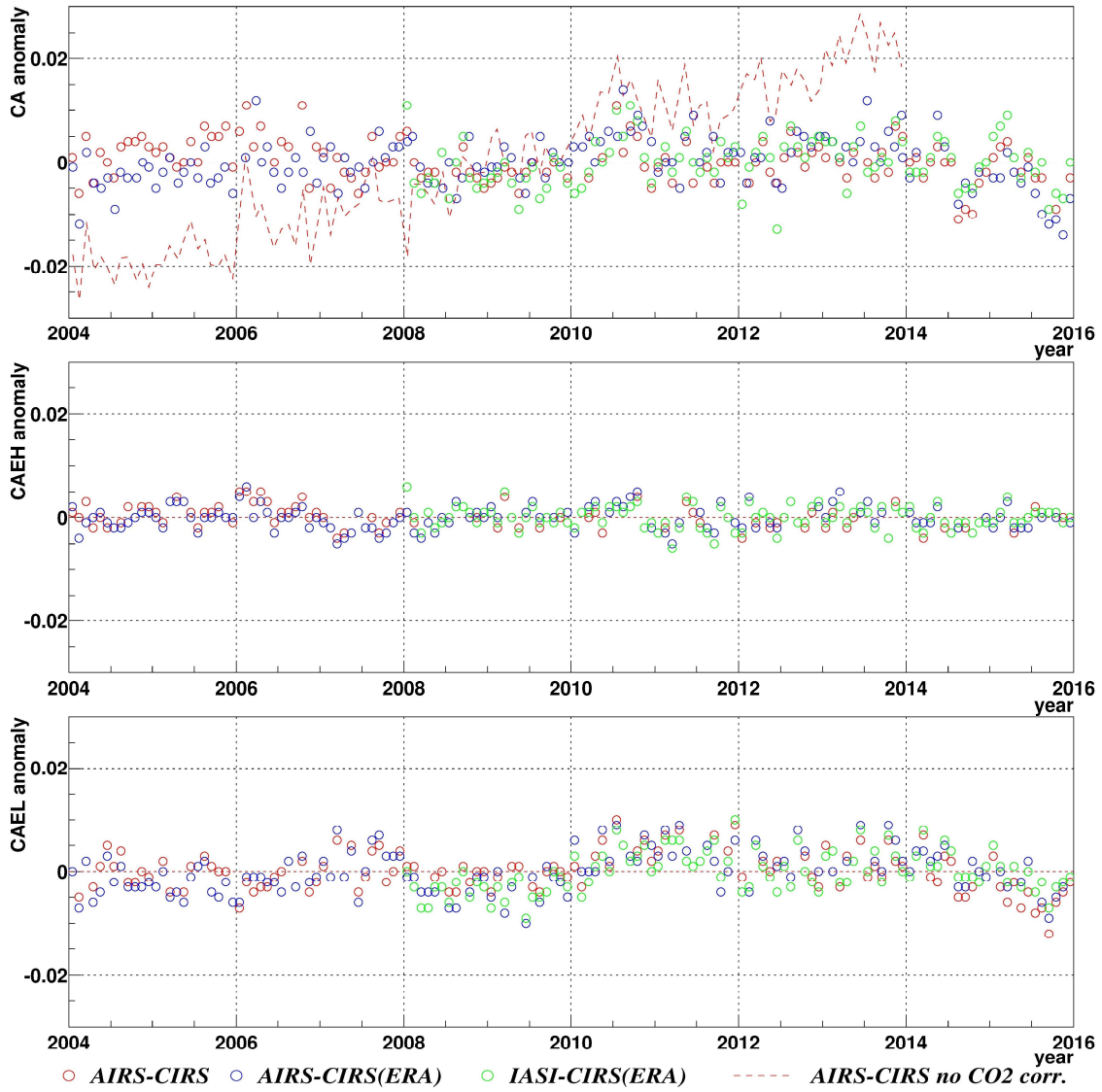
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2 Figure 8. Annual mean zonal distributions of CA, CAH and CAL (left) and CAE, CAEH and CAEL
 3 (right). Results are compared between AIRS-CIRS, using ancillary data from AIRS-NASA and from
 4 ERA-Interim, IASI-CIRS and AIRS-LMD.

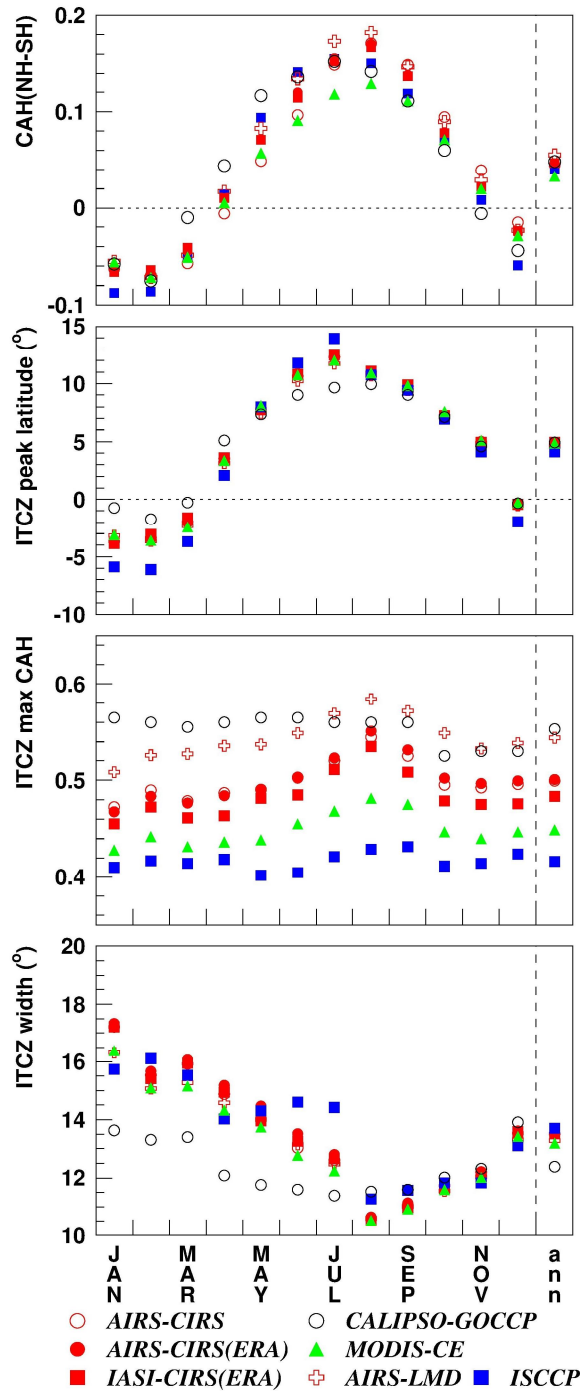
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1
 2 Figure 9. Top: Geographical maps of annual CAH (left) and CAL (right), from AIRS-CIRS (2003-2015,
 3 top), ISCCP (2003-2007, middle) and CALIPSO-GOCCP (2007-2008, bottom), the latter two from the
 4 GEWEX Cloud Assessment data base.
 5

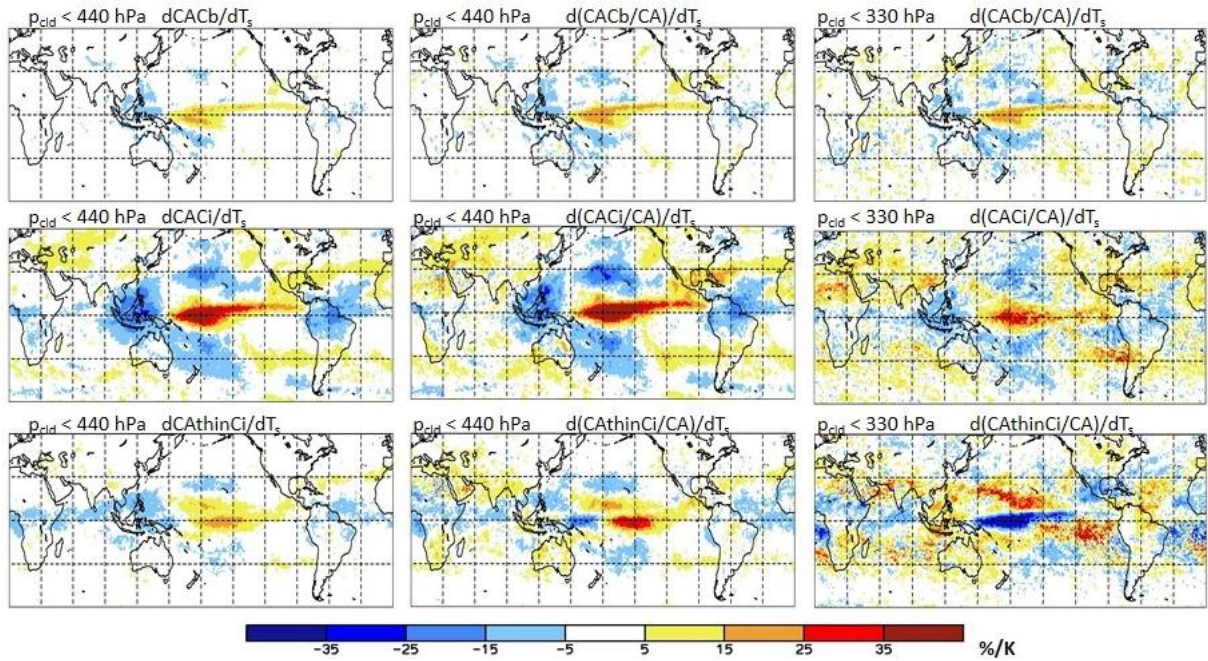


2 Figure 10. Time anomalies of deseasonalized CA, CAEH and CAEL over the globe. In the case of CA,
 3 additional values are shown without calibration of spectral atmospheric transmissivities for changes in
 4 atmospheric CO₂ concentration.



1

2 Figure 11. Seasonal cycle / annual average of (1) CAH differences between NH hemisphere (0°-60N)
 3 and SH hemisphere (0°-60S), (2) ITCZ peak latitude, (3) maximum CAH within ITCZ and (4) width of
 4 ITCZ.



1
 2 Figure 12. Geographical maps of linear regression slopes between monthly mean anomalies in amount
 3 of Cb ($\varepsilon_{cld} > 0.95$, top row), Ci ($0.95 > \varepsilon_{cld} > 0.4$, middle row) and thin Ci ($0.4 > \varepsilon_{cld} > 0.1$, bottom row)
 4 from AIRS-CIRS and global mean surface temperature anomalies from ERA-Interim; left: $p_{cld} < 440$
 5 hPa, middle: relative cloud amount, right: $p_{cld} < 330$ hPa and relative cloud amount. Results using 156
 6 months during the period 2003-2015.