Simple Climate-Level Retrieval Example: Cloud Fraction

August 18, 2020

1 Introduction and Context

An extremely simple algorithm for cloud fraction (over ocean) is presented here, partially as a proxy, or example, for examining the best methods for creating useful, long-term climate data records with hyperspectral sensors. A fundamental concern is that during the last 20 years AIRS has concentrated on just one type of retrieval and really, just 2-3 products, that are primarily weather and process related. Brian Kahn's cirrus cloud retrieval algorithm might be an exception to this somewhat general statement. These extremely well calibrated radiances, coupled with our ability to very precisely match AIRS to CrIS (via CHIRP), begs for development of products that can withstand the scrutiny that future climate data records will receive. For example, I have already shown that the AIRS surface temperature record may have inaccurate trends at the 35% level, which may be more a calibration rather than retrieval issue.

Long-term continuity records by nature often require a detailed understanding of both their accuracy and stability (precision). A lien on the existing Level 2 products is aliasing in sampling, since retrievals are not always possible. CLIMCAPS may address this quite nicely by using MERRA-2 as it's a-priori. But, at the moment, continuity has not been explicitely addressed in any of our products. CLIMCAPs is very different from the AIRS V7 retrieval, especially with regard to a-priori information, but also since it uses a different RTA (different spectroscopy) and does not explicitly take radiometric differences between instrument into account, much less spectral differences.

This report just illustrates that some extremely important climate data records using very simple algorithms are possible with hyperspectral sensors. These types of algorithms should be relatively inexpensive to create and produce. Maybe they can be done by end users, but *only* if users can be relieved of handling 200+TB of data to just get started. I think this is the time to examine these issue to ensure that future researchers can use these data easily, or that we produce several well understood products that can be sold to the climate community.

For example, maybe we need to produce Level 1 radiances that are either gridded in some way, or that are stored so that a user can easily download the full time series for a small spatial grid cell. This would help users start to look at these data and understand their utility. In the future, data saved in this way might make new algorithms concentrating on anomalies much easier to produce and test in the cloud, etc. etc.

When I started this work I was under the (false) impression that the VIIRS cloud products (esp. cloud fraction) were not provding the continuity required with MODIS. I believe that was initially a problem, but it appears that the MODIS/VIIRS community has worked very hard to clear up these problems. It probably helps the cloud fraction, examined here, is less sensitive to absolute calibration than other cloud products. However, I would like to point out that the VIIRS cloud mask group has produced very detailed documentation *already* on continuity of their products. We have not.

2 PDF-based Cloud Fraction Retrievals using AIRS

The AIRS brightness temperature (BT) depression by clouds is one measure of cloud radiative forcing (CRF),

$$CRF = BT_{\text{obs}} - BT_{\text{clear}} \tag{1}$$

We estimate BT_{clear} using

$$BT_{\text{clear}} = (SST - \Delta BT_{\text{atmosphere}}) \tag{2}$$

where $\Delta BT_{\text{atmosphere}}$ is the BT depression relative to the surface temperature for clear scenes. The BT depression for each AIRS measurement is estimated from the observed BT differences between the 1228 cm^{-1} channel, a weak water vapor line, and from the 1231 cm^{-1} channel, a relatively transparent window channel that still has significant water vapor continuum absorption. The regression is soley a function of the BT difference between these two channels,

$$\Delta BT_{\text{atmosphere}} = \mathbf{F}\left(BT_{1228\ \text{cm}^{-1}} - BT_{1231\ \text{cm}^{-1}}\right). \tag{3}$$

where **F** is a 3rd or 4th order polynomial that is derived from a large set of simulated AIRS spectra using ECMWF model fields.

The full AIRS radiance record for these two channels was collected into a set of 64x120 latitude/longitude equal-area grids (which was probably a mistake), each 16-days long. For the present work, only ocean scenes were studied, since a reasonably good surface temperature estimate is needed to compute the AIRS cloud fraction. In addition, these PDFs combine both ascending and descending orbits, for now. Each observation was matched to the well-known NOAA OISST SST climatology data set. The PDF of the CRF observations was computed on a rather large, coarse grid for this initial test, namely -140 to +70K in 2K increments. CRF forcings above zero are indicative of AIRS measurement errors, RTA errors, and/or poor SST estimates, and in general were extremely rare. In future work a much finer CRF grid will be used, especially in the -10 to +5 K region.

The cloud fraction (CF) is estimated for each grid cell for a 16-day period by summing the CRF PDF from max negative forcing (-140K) to a cutoff denoted as α below,

$$CF = \sum_{\alpha}^{-140K} \text{PDF}_{\text{CRF}}. \tag{4}$$

Since there are very few clouds with low CRF, reasonable results are obtained using α = -4 to -6K. Comparisons of the AIRS CF to MODIS CF using 1-year averages suggested that α = -4.5K was optimum. The following table shows how the global AIRS CF varies with α. Studies of long-term trends in CF

Table 1: Global mean (over ocean) cloud fraction (CF) as a function of the PDF integration limit α.

α (K)	Mean CF
0	0.999
-2	0.976
-4	0.770
-6	0.649

using this approach will be affected by inaccurate trends in the AIRS radiometric stability and in the surface temperature climatology used to estimate the clear scene BT. Recent work has shown that AIRS is stable to ~0.002K/year. The stablilty of the OISST SST climatology is less clear, but is likely well below 0.01K/year.

Since this CF algorithm is exceedingly simple, experiments to determine the sensitivity of the CF trends to input uncertainties is trivial, and take just seconds to minutes on a desktop computer.

For example, if the AIRS radiometry drifts by 0.002K/year, we find that this translates into a drift in the CF of ~0.016%/year or 1.2% over 20 years. However, note that recent studies (Norris) of CF trends compared to climate model do *not* use absolute CF trends, but only how those trends vary with latitude, since climate models cannot as yet compute accurate CF trends.

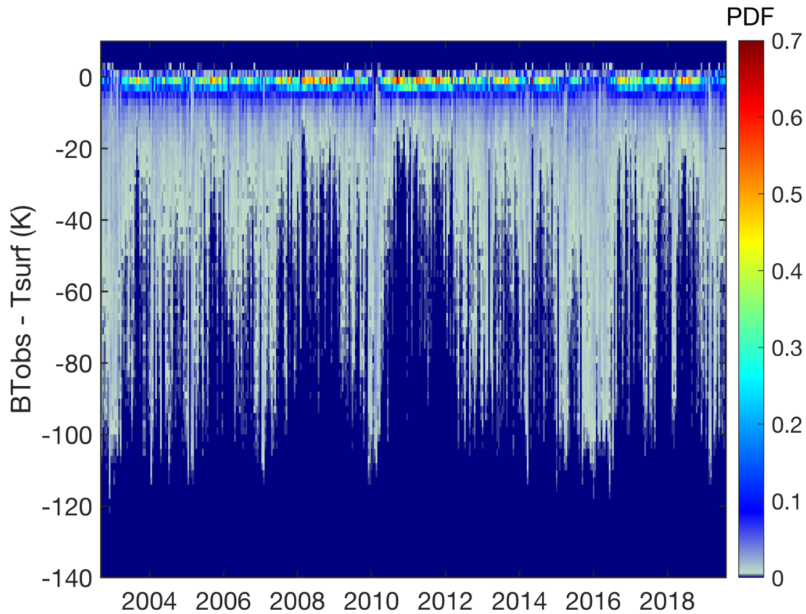

Figure 1: A sample time series of cloud radiative forcing (CRF) PDFs for a single grid cell in our climatology, located in the Atlantic ocean west of Africa at (1.8,3.0)° lat/lon. The rather high values of deep cloud forcing is very evident. Note the color scale is chosen to highlight low values in the PDF.

3 Absolute Cloud Fraction

Figure 2 shows the CF for this work (Strow), from MODIS, and the AIRS Level 3 CF. From now on, we will denote the AIRS CF to be the CF derived here, and the AIRS Level 3 CF to be the AIRSL3 CF. Clearly there is good quantitative agreement between AIRS and MODIS CF. The AIRSL3 CF is about 0.28 lower than our CF result and that of MODIS.

Figure 3 whos the yearly mean difference between the MODIS and AIRS CF, and between MODIS and the AIRSL3 CF *after* a constant value of 0.28 is added to the AIRSL3 CF (which puts the global mean difference between these two CFs to zero). Most of the MODIS and AIRS CF differences are well below 0.1. We believe that our AIRS CF algorithm probably needs some adjustments for high latitudes, where low clouds are more common, likely making our value for α of -4.5K too negative to catch all clouds. Therefore we onlly make statistical intercomparisons between ± 60° latitude. For MODIS - AIRS CF we get a mean difference of zero (by definition via the selection for the value of α) with a standard deviation of 0.03 in CF. The MODIS versus AIRS L3 CF differences are much larger, as seen in Fig. 3 (after adding 0.28 to the AIRSL3 CF), in some regions as large as -0.3, but mostly peaking in the ± 0.1 level, with the larger differences in regions of high clouds and regions with low marine boundary layer clouds and stratus.

4 Cloud Fraction Trends

Figure 4 shows the 17-year CF trends, in units of %CF/yr, for AIRS, MODIS, and AIRS L3. There is a high degree of similarity, and the AIRS L3 CF trend appears to not be too affected by the 0.28 deficit in it's CF. Both AIRS CF trends are slightly higher than MODIS. The AIRSL3 CF trend is generally higher

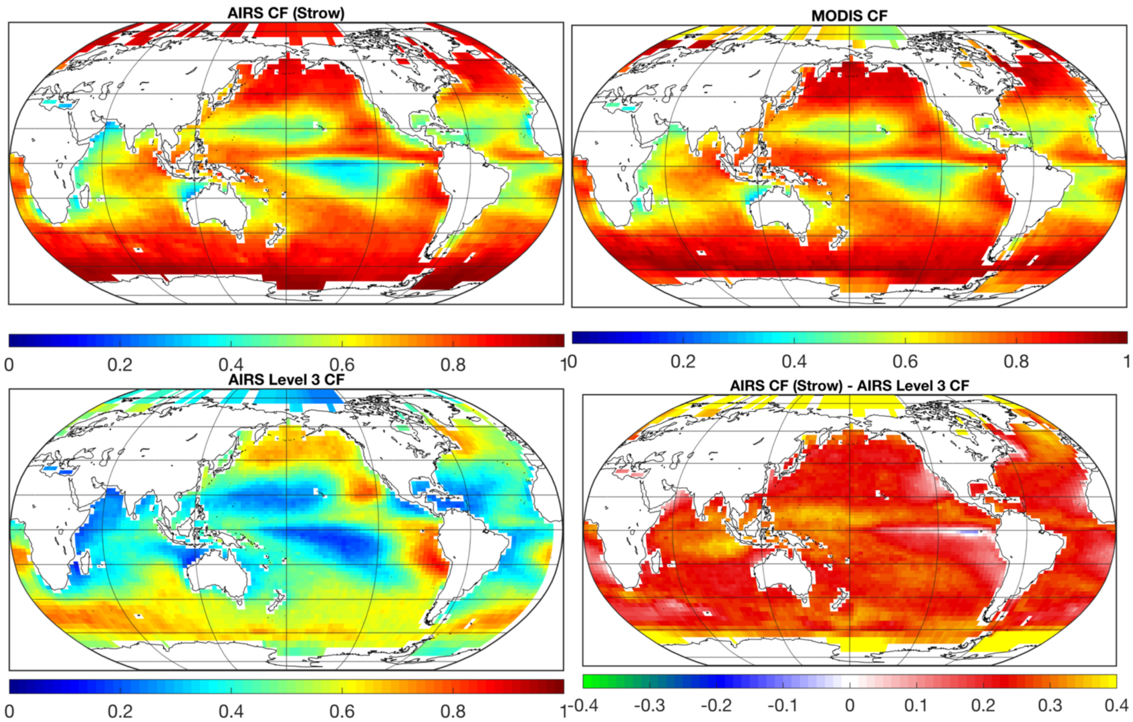

Figure 2: One year (2007) averaged cloud fraction from this work (AIRS CF (Strow)), MODIS, and from the AIRSL3 CF. Also shown in the difference between the AIRS CF (Strow) and the AIRSL3 CF in the lower right panel.

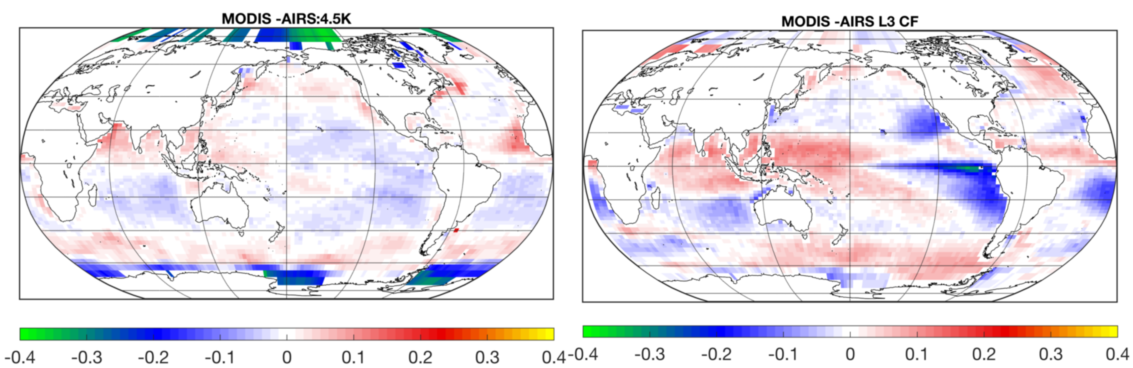

Figure 3: Differences between MODIS and AIRS mean 2007 cloud fraction. The right hand panel is MODIS - (AIRS L3 CF + 0.28), to account for the large offset in the AIRS L3 CF relatively to our AIRS CF and MODIS.

than both the AIRS CF and MODIS trends in the mid-latitude southern oceans. Grid cells for the AIRS CF with trends more than 2X larger than the trend uncertainty (2-σ) are marked with + signs.

The ± 60° average CF trend for AIRS is -0.0177 %/yr with a standard deviation of 0.15%/year. The same statistic for MODIS is -0.0095 %/yr with a 0.13% standard deviation. The difference between the AIRS and MODIS mean trends is -0.008%/yr (MODIS - AIRS), which is about 2X smaller than our estimated AIRS CF accuracy from above (0.016%/yr) if AIRS is inaccurate solely due to radiometric drift (ignoring SST trend errors). This is a remarkable results, especially given the absolute simplicity of the AIRS CF algorithm and it essentially zero CPU requirements. These results might suggest that non-polar global cloud cover is getting smaller, although 17-years may be too short a time period for this measurement. The trend patterns appear to have some ENSO-like patterns which are not averaged out in 17 years.

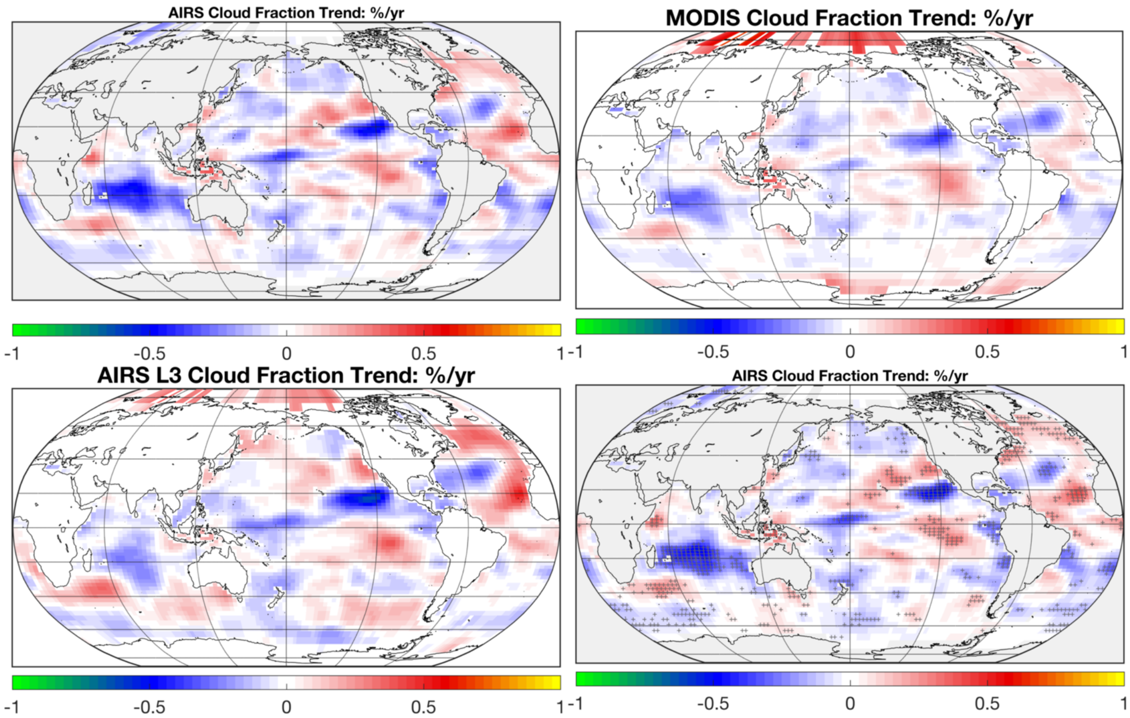

Figure 4: 17-year cloud fraction trends in %CF/year (colorscale). The AIRS CF developed here is in the top left panel, the MODIS CF trend in the top right panel, and the AIRSL3 CF trend in the lower left panel. Both AIRS CF trends are slightly higher than MODIS. The AIRSL3 CF trend is generally higher than both the AIRS CF and MODIS trends in the mid-latitude southern oceans. The lower right panel is the same as the upper left panel, except that grid cell with trends more thatn 2X larger than the trend uncertainties are marked with a +.

These results might suggest that a new approach to retrieving cloud fraction with AIRS is unwarranted. However, having two independent measurements of the same parameter is an important consideration in any climate trend analysis. In addition, there are some differences in these products, which we highlight by looking at the zonal CF trends for AIRS and MODIS.

Figure 5 plots the zonal CF trends for AIRS and MODIS using the data show in Fig. 4. They exhibit some similarity, but there are significant differences in regions of tropical descending air where CFs are relatively low. In the S. Hemisphere AIRS has about 2X larger negative trend, while in the N. Hemisphere MODIS has about a 2X larger negative trend. The S. Hemisphere negative trends might be dominated by the Pacific ocean west of Australia, where our AIRS CF show larger negative trends than MODIS. More work, of course, is needed in order to see if these differences are real, and if one data set is more accurate than the other.

Cloud forcing trends require long time periods for effective measurements, and therefore must cross instrument boundaries. A quick look at this for both the hyperspectral sounders (AIRS, CrIS) and for the imagers (MODIS, VIIRS) suggests that we are in good shape with regard to continuity. (Note that I have not looked at the CLIMCAPS cloud fraction, which is not yet available in Level 3 format.) The left panel of Fig. 6 shows yearly differences (2018) between AIRS CF and a similar CF we derived from a 1% subset of CrIS radiances. Similarly the right panel of Fig. 6 shows the 2018 year mean differences between the MODIS and VIIRS CF Level 3 products. The agreement for both our CF agreement between platforms and for the MODIS vs VIIRS is excellent, with mean CF differences in the 0.01 range with a standard deviation of 0.01 in CF. It remains to be seen how similar the AIRS and CLIMCAPS Level 3 CF products compare.

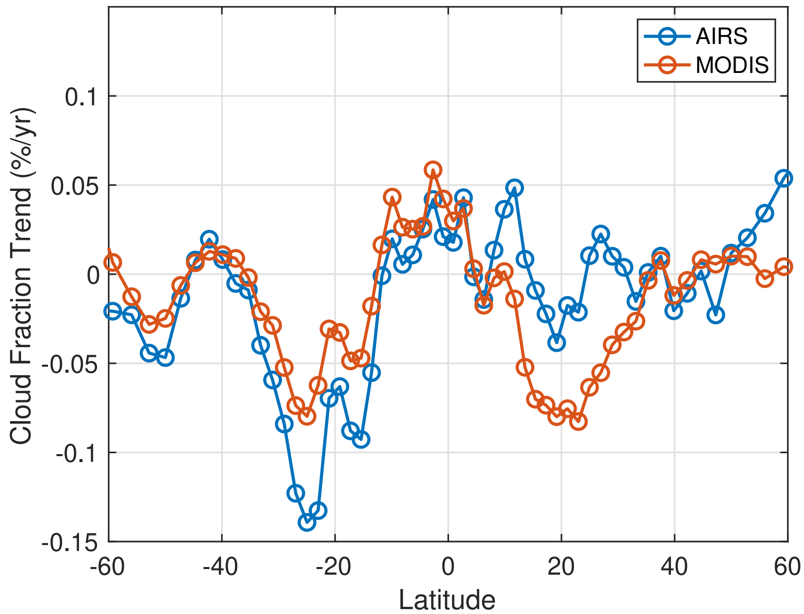

Figure 5: Zonal 17-year CF trends from AIRS and MODIS, in units of %CF/year.

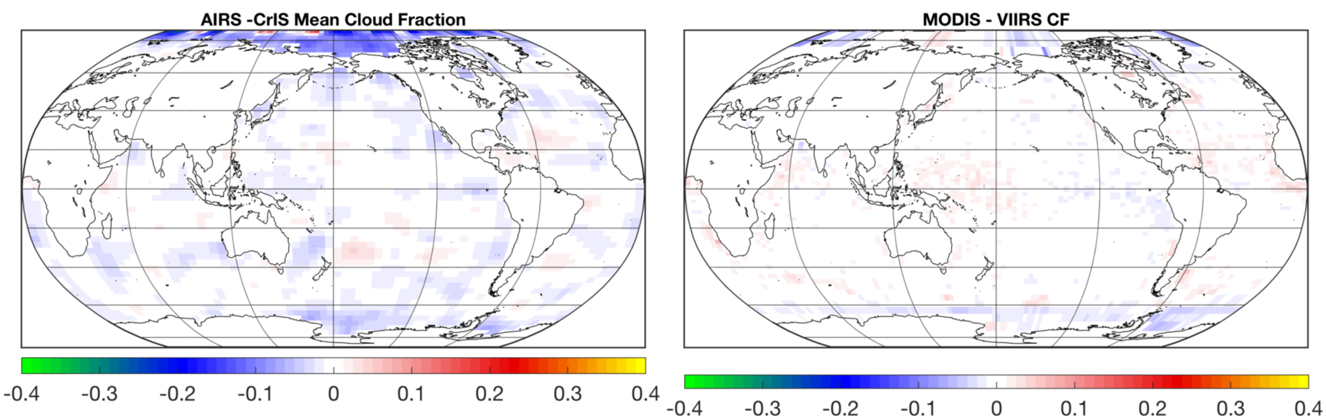

Figure 6: Yearly mean differences in CF between AQUA and NPP instruments. Left: AIRS CF minus SNPP-CrIS CF, Right: MODIS - VIIRS CF.

5 Cloud Fraction Anomalies

Cloud fraction anomalies were created from the Level 3 CF data set time series. Although not shown here, the anomaly correlation between the AIRS and MODIS CFs are quite uniform globally and are generally in the 0.8 range (this is prelminary, since I used MODIS day anomalies compared to AIRS night+day anomalies! High anomaly corrections might result if this is fixed.)

Figure 7 shows the 17-year standard deviations for AIRS CF, MODIS CF, and AIRSL3 CF. Again, this is preliminary since the AIRS CF is ascending/descending combined, while the MODIS and AIRSL3 are ascending only. (This difference does NOT appear in the absolute CF intercomparisons or in the CF trends, where ascending and descending were combined for CF from all instruments.)

The AIRS CF anomaly standard deviations are somewhat larger than those for MODIS and AIRSL3. If the MODIS colorscale is compressed by 30% the MODIS standard deviations appear extremely similar to those for the AIRS CF. At present, we are uncertain if this ia a true difference, or if this is due to using day-only (quite likely?) for MODIS and AIRS L3 CF.

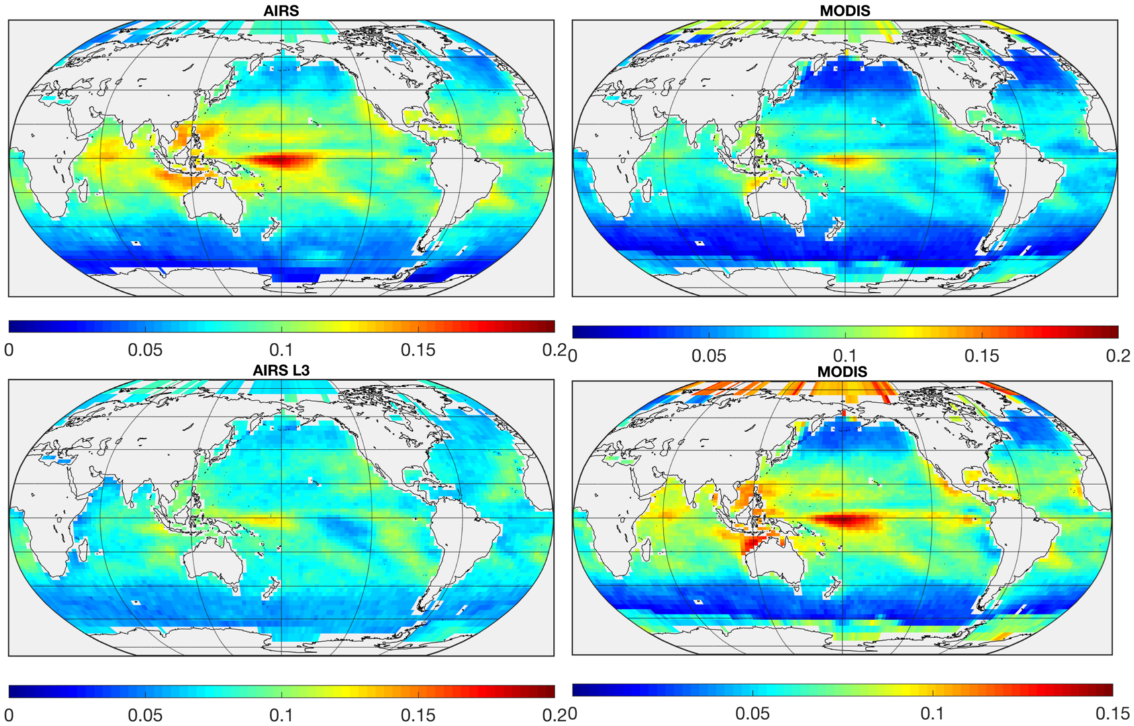

Figure 7: Standard deviation (over 17-year) for monthly averaged CF for AIRS, MODIS, and AIRSL3 cloud fraction anomalies. In the lower right panel the colorscale for MODIS has been compressed by 30% compared to the other panels.

6 Simple PDF Forcing Vertical Trends

The summation of PDF_{CRF} done in Eq. 4 removes all vertical information content about CRE. Admittedly, even this PDF_{CRF} is a bit crude in that it comes from only one channel, so that thin cirrus forcing cannot be separated from low water cloud forcing. However, PDFs with high CRF are certainly from high deep clouds. There are a host of ways to add more information content to these types of measurements, such as using more opaque channels to mask low clouds, using other data to classify cloud-types in each scene before doing a statitical analysis, and using channel linked histograms to detect cirrus, dust, ash, etc.

However, even this simple CRF metric may lead to some scientific insights, especially with regard to trends and anomalies. An quick example of trends in the PDF_{CRF} data set is shown in Fig. 8. The left panel shows the zonal PDF_{CRF} values, again using a color scale the emphasized the low values so that high deep cloud occurances can be seen. This can be used as a reference to understand the right panel, which shows the trends in PDF_{CRF}, *normalized* by the pixel mean, ie the PDF trend = 100*(PDF_trend(cloud forcing, latitude))/(PDF(cloud forcing, latitude)).

Although the polar spatial resolution is limited, we see higher low (low BT) clouds in the Arctic. Regions of subsistence have fewer low (or low BT forcing) clouds although what are likely extremely low clouds increase in these regions in the N.H. but decrease in the S.H (small changes above zero forcing). Most prominent is the increase in convection, especially in the N.H. low-tropics, where the signals are often more than 2X the uncertainties.

Patterns of these types can of course be examined by season, with ENSO, and other ocean circulation types. However, the real value of this approach is likely in the context of long-term trends where known uncertainties and algorithm simplicity offer major advantages over other approaches.

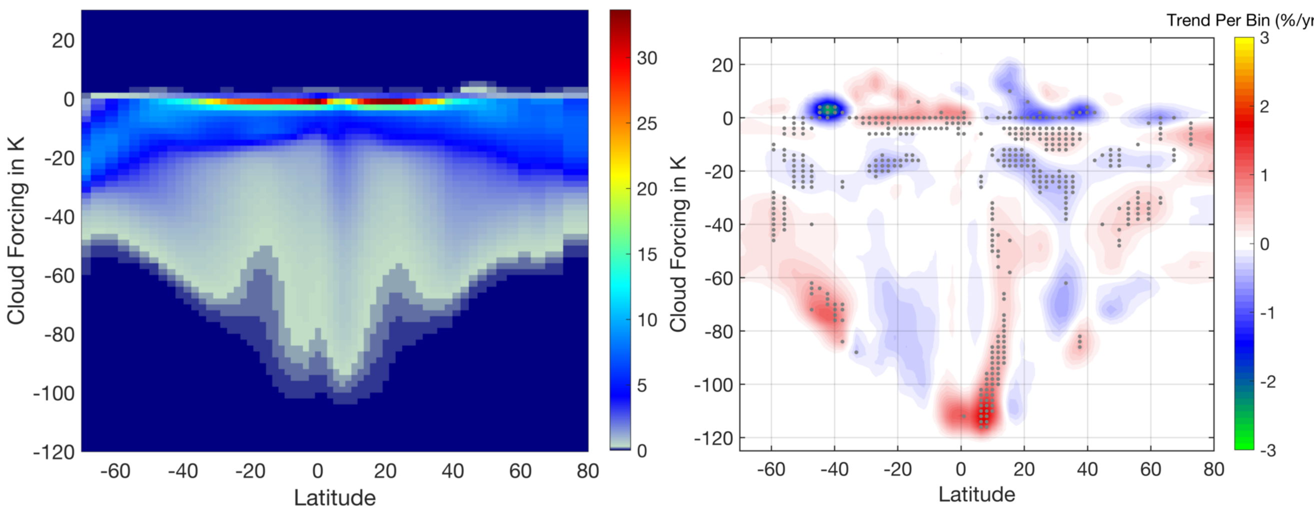

Figure 8: Left Panel: Zonal cloud radiative forcing (CRF) PDF yearly means, Right Panel: CRF PDF relative trends per pixel, in %/year. Regions with trends that are 2X the magnitude of the 2-σ trend uncertainties are marked with + signs.