Spectrally resolved fluxes derived from collocated AIRS and CERES measurements and their application in model evaluation, Part II: cloudy sky and band-by-band cloud radiative forcing over the tropical oceans

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Abstract

We first present an algorithm for deriving cloudy-sky outgoing spectral flux through the entire longwave spectrum from the collocated AIRS and CERES measurements over the tropical oceans. The algorithm is similar to the one described in the Part I of this series of studies: spectral angular dependent models are developed to estimate the spectral flux of each AIRS channel then a multivariate linear prediction scheme is used to estimate spectral fluxes at frequencies not covered by the AIRS instrument. The entire algorithm is validated against synthetic spectra as well as the CERES OLR measurements. Mean difference between the OLR estimated in this way and the collocated CERES OLR is 2.15 Wm$^{-2}$ with a standard deviation of 5.51 Wm$^{-2}$. The algorithm behaves consistently well for different combinations of cloud fractions and cloud-surface temperature difference, indicating the robustness of the algorithm for various cloudy scenes. Then, using the GFDL AM2 model as a case study, we illustrate the merit of band-by-band cloud radiative forcings (CRFs) derived from this algorithm in model evaluation. The AM2 tropical annual-mean band-by-band CRFs generally agree with the observed counterparts, but some systematic biases in the window bands and over the marine-stratus regions can be clearly identified. An idealized model is used to interpret the results and to explain why the fractional contribution of each band to the broadband CRF is worthy for studying: it is sensitive to cloud height but largely insensitive to the cloud fraction.
1. Introduction

The part I of this series of study [Huang et al., 2008] introduced an algorithm of deriving spectral fluxes at 10cm\(^{-1}\) spectral interval over the entire longwave spectrum from collocated AIRS (Atmospheric Infrared Sounder) and CERES (the Cloud and the Earth’s Radiant Energy System) clear-sky observations over the oceans. It also used the GFDL AM2 simulation as a case study to demonstrate the merit of such band-by-band clear-sky fluxes in GCM (general circulation model) evaluation. As a natural continuation, in this study we present a similar algorithm for deriving such spectral fluxes and then band-by-band fluxes from collocated AIRS and CERES cloudy-sky observations over the tropical oceans. The merits of spectral fluxes in model evaluations have already been discussed and demonstrated in Huang et al. [2006] and Huang et al. [2008]. While both studies dealt with the clear-sky band-by-band fluxes, even more meaningful are the band-by-band cloud radiative forcings (CRFs) [i.e., the differences between clear-sky and all-sky fluxes over each individual bands\(^1\)]. Wien’s displacement law indicates that the peak of blackbody radiation shifts towards the lower frequency when the temperature decreases. Therefore, absolute amount of cloud emission over any given band is sensitive to its cloud top temperature, so does the fractional contribution to the longwave broadband cloud emission. Moreover, the spectrally-dependent extinction coefficients of liquid and ice clouds are generally different and gradually vary from one band to another.

\(^1\) The “band” in “band-by-band” refers to the band with a band width at the order of magnitude of 100cm\(^{-1}\), e.g. those bands used in GCM longwave radiation schemes.
Therefore, band-by-band CRFs contain much more information than the broadband CRF. Moreover, it is the contributions from water vapor and temperature (which are tightly coupled to each other via clear-sky water vapor and lapse-rate feedbacks) and clouds that are ultimately responsible for the needed outgoing longwave fluxes at TOA to balance the net incoming shortwave fluxes. Given the fact that water vapor and clouds have distinctively different spectral absorption features, the band-by-band fluxes and CRFs potentially could be of insightful help in unveiling how the water vapor and clouds interplay with each other to attain such needed OLR variations. As modeling of clouds still is one of the major issues that plague the advance of climate modeling [Stephens, 2005; Bony et al., 2006; Soden et al., 2006], various techniques have been applied to diagnose observed and simulated clouds in innovative ways, e.g. compositing cloud process based on synoptic conditions [e.g. Lau & Crane, 1995, 1997; Tselioudis et al., 2000; Norris & Iacobellis, 2005] and applying statistical cloud classifications [e.g. Jakob et al., 2005; Rossow et al., 2005; Xu et al., 2005, 2007, 2008, 2009; Luo et al., 2007; Zhang et al., 2007]. While these techniques focus on extracting coherent spatial information of cloud systems, band-by-band CRFs are aiming at the spectral information of clouds and provide another insightful dimension to understand and diagnose the observed and simulated clouds.

The rest sections are organized as follows. Section 2 depicts the satellite datasets and the modeling tools. Section 3 describes the algorithm, the validation, and the examination of the error characteristics for different types of cloudy scenes. Section 4 presents the
band-by-band CRFs as derived from collocated AIRS and CERES observations in 2004 and a model-observation comparison of the annual-mean band-by-band CRFs. An idealized model with one layer of cloud is used in section 4 to interpret the band-by-band CRFs and to illustrate the merit of fractional contribution of each band to the broadband CRF. Discussions and conclusions are then given in section 5.

2. Datasets, models, and algorithms

The satellite datasets and modeling tools used here are identical to those used in the part I of this study. Therefore, except facts related to cloudy-sky observations and related modeling issues, the rest are only briefly summarized and further information can be found in Huang et al. [2008] and references there-in.

2.1 CERES and AIRS and collocation strategy

Two identical CERES instruments (FM3 and FM4) are aboard the NASA Aqua spacecraft. The instrument field of view (IFOV) of CERES is about 20km nadir-view footprint on the surface. Only CERES observations from the cross-track scanning mode are used in this study since AIRS always operates in the cross-track scanning mode. CERES fluxes are derived based on unfiltered radiances and corresponding angular distribution models (ADMs) [Loeb et al., 2001; Loeb et al., 2003; Loeb et al., 2005; Loeb et al., 2007]. The CERES dataset used in this study is the Aqua-CERES level 2 footprint data product, the Single Satellite Footprint (SSF) TOA/Surface Fluxes and Clouds Edition 2A. Loeb et al. [2005] described the scene-type classification and constructions of ADMs in detail. Only a brief summary is given as follows. The CERES SSF algorithm
classifies cloudy-sky footprints over the oceans in the following ways: cloudy footprints are first stratified into discrete intervals of precipitable water \((pw, 4 \text{ bins})\) retrieved from SSM/I (Special Sensor Microwave Imager) [Goodberlet, et al., 1990], cloud fraction \((f, 4 \text{ bins})\) as determined from collocated MODIS imagery [Minnis et al., 1998], surface-cloud temperature differences \((\Delta T_{sc}, 22 \text{ bins})\) as described in Minnis et al. [1998], and image-based surface skin temperature \((T_s, 11 \text{ bins})\). Detailed definitions of these discrete intervals are summarized in Table 1. In total 3872 discrete intervals have been defined in this way. In practice, the CERES SSF data that we examined shows that 2008 discrete intervals are enough to describe all possible cloudy-sky scenes observed over the oceans.

For each discrete interval, a pseudoradiance parameter \((\psi)\) is further defined (equation 15 in Loeb et al. [2005]) to depict the combined influences of cloud parameters (i.e. cloud top temperatures, cloud fractions, and cloud emissivities) and surface parameters (i.e. surface temperatures and emissivities) on the TOA outgoing radiances in the absence of gas absorbers:

\[
\psi(T_s, T_c, f, \varepsilon_s, \varepsilon_c) = (1 - f)\varepsilon_s B(T_s) + \sum_{j=1}^{2} [\varepsilon_s B(T_s)(1 - \varepsilon_{cj}) + \varepsilon_{cj} B(T_{cj})]f_j
\]

in which \(f_j\) is the cloud fraction of the \(j\)-th cloud layer within a scene \((f = f_1 + f_2)\), \(T_{cj}\) and \(\varepsilon_{cj}\) are the cloud top temperature and cloud infrared emissivity of the \(j\)-th layer, respectively, \(\varepsilon_s\) is the surface infrared emissivity, and \(B(T) = \frac{1}{\pi} \sigma T^4\) where \(\sigma\) is the Stefan-Boltzmann constant. Furthermore, for each 3° view zenith angle bin of a given discrete interval, the relationship between radiance \((I)\) and \(\psi\) is defined with a
predetermined third-order polynomial fit. Hence, radiances can then be integrated over all
zenith angles to produce a flux and the anisotropy factor can be directly computed [Loeb
et al., 2005]. Using such angular-distribution models (ADMs) significantly reduces both
the bias and the root-mean-square (RMS) errors of LW TOA flux. Loeb et al. [2007]
estimated a bias of 0.2-0.4 Wm\(^{-2}\) and RMS error < 0.7 Wm\(^{-2}\) for Aqua-CERES regional
mean LW TOA flux.

AIRS is also aboard Aqua [Aumann, et al., 2003]. It is a grating spectrometer
recording radiances at 2378 channels across three bands (3.74-4.61\(\mu\)m, 6.20-8.22\(\mu\)m,
8.8-15.4\(\mu\)m) with a resolving power \((\lambda/\Delta\lambda)\) of 1200. AIRS scans from -49\(^{\circ}\) to 49\(^{\circ}\) with a
nadir-view footprint of 13.5km on the surface. It provides an unprecedented data source
of the outgoing thermal IR spectra with excellent calibration and dense global coverage
[Chahine et al., 2006]. In this study we use the AIRS geo-located and calibrated radiances
(level 1B). Among the 2378 AIRS channels, only those recommended by the AIRS team
for level-2 retrieval purposes are used. AIRS radiances from the near-IR band,
3.74-4.61\(\mu\)m (2169-2673 cm\(^{-1}\)), are not used because of its nearly negligible contribution
to the longwave flux. In addition, AIRS data was screened with a strict quality control
procedure to exclude possible bad spectra as done in Huang & Yung [2005]. As for
collocating AIRS and CERES individual observations, the criteria adopted here are
identical to Huang et al. [2008], i.e., (1) the time interval between AIRS and CERES
observations is within 8 seconds, and (2) the distance between the center of an AIRS
footprint and that of a CERES footprint on the surface \((\Delta_{airs-ceres})\) is less than 3km. In this
study, we analyze the collocated AIRS and CERES cloudy-sky observations over the tropical oceans (30°S-30°N) in the entire year of 2004

2.2 Models

2.2.1 Forward radiative transfer model

A forward radiative transfer model is needed to construct spectral ADMs suitable for the AIRS channels and to estimate spectral fluxes at frequencies not covered by the AIRS instrument, MODTRAN™-5 version 2 revision11 (hereafter, MODTRAN5) is used here for this purpose. Collaboratively developed by Air Force Research Laboratory and Spectral Sciences Inc [Berk, et al, 2005], MODTRAN5 inherits the flexibility in handling clouds from its predecessors but significantly improves the spectral resolution to as fine as 0.1cm⁻¹. Comparisons between MODTRAN5 and a line-by-line radiative transfer model, LBLRTM [Clough and Iacono, 1995; Clough, et al., 2005], showed agreement up to a few percent or better in the thermal IR transmittances and radiances [Anderson et al., 2006]. In this study, synthetic AIRS spectrum is done by convolving the MODTRAN5 output at 0.1cm⁻¹ resolution with the spectral response functions of individual AIRS channels [Strow, et al., 2003; Strow, et al., 2006].

2.2.2 GFDL AM2

To illustrate the application of band-by-band CRFs in GCM evaluation, we use a version of AM2 (am2p14), the atmospheric GCM developed at NOAA Geophysical Fluid Dynamics Lab (GFDL). AM2 treats cloud quantities such as cloud liquid water, cloud ice amount, and cloud fraction as prognostic variables. The shortwave and longwave
radiation parameterizations follow *Freidenreich & Ramaswamy* [1999] and *Schwarzkopf & Ramaswamy* [1999], respectively. The longwave radiation scheme parameterizes radiative fluxes over eight spectral bands. The TOA flux and CRF of each band can be directly evaluated against the counterparts derived from the collocated AIRS and CERES observations. A detailed description of AM2 can be found in *GFDL GAMDT* [2004]. We run the AM2 model with observed monthly SSTs from 2000-2007. Given that the observational analysis focuses on the year of 2004, here only model output in 2004 are analyzed.

3. Algorithm and validations

3.1 Algorithm

The algorithm is in principle identical to the one depicted in part I [Huang et al., 2008], which consists of two steps: (1) constructing a spectrally-dependent ADM to convert spectral radiance to spectral flux at each AIRS channel and (2) estimating the spectral fluxes at frequencies not covered by the AIRS instrument.

3.1.1 Spectral ADM for each AIRS channel

The centerpiece of spectrally-dependent ADM is the spectrally-dependent anisotropic factor, defined as

\[ R_s(\theta) = \frac{\pi I_u(\theta)}{F_v} \]  

where \( I_u(\theta) \) is the TOA upwelling radiance at frequency \( v \) along viewing zenith angle \( \theta \) and \( F_v \) is the TOA upwelling spectra flux at the same frequency \( v \). For each predefined
scene type, once $R_v(\theta)$ is determined, then spectral flux can be obtained from the
measured $I_v(\theta)$.

Similar to the part I, ECMWF ERA-40 reanalysis [Uppala, et al., 2005] in
conjunction with the MODTRAN5 are used to derive $R_v(\theta)$. While CERES clear-sky
ADM over the oceans contains only 14 discrete intervals of precipitable water, lapse rate,
and surface skin temperature, its cloudy-sky ADM contains 2008 out of 3872 discrete
intervals as described in section 2.1 and Table 1. Using pseudoradiiances in the CERES
cloudy-sky ADMs adds further computational cost for simulating spectra and deriving $R_v(\theta)$ for each AIRS channel. To make computation affordable while still retaining
maximum consistency with the CERES ADMs, following approach is adopted for
carrying out the simulation. As in the part I [Huang et al., 2008], we still use four months
of ECMWF data over the tropical oceans (i.e. 2001 October, 2002 January, April, and
July). For each month, four 6-hourly ECMWF ERA-40 fields between 60°S-60°N oceans
are randomly chosen and then temperature and humidity profiles over each oceanic grid
box are categorized according to its precipitable water ($pw$) and surface skin temperature
($T_s$). Second, for each possible jointed discrete interval of $pw$ and $T_s$, 1200 randomly
chosen profiles (or all profiles when the total number of profiles in that category is less
than 1200) are archived for the next step. Third, for each archived profile, clouds are then
specified with varying cloud top height and cloud fraction so that each individual discrete
interval of $(pw, T_s, f, \Delta T_{sc})$ is covered. Fourth, for each cloudy profile generated at the
previous step, cloud emissivity is further varied to produce different pseudoradiance. In
original CERES SSF algorithm, $\psi$ varies from 1 to 250 Wm$^{-2}$ sr$^{-1}$ with a step size of 1 Wm$^{-2}$ sr$^{-1}$. To save computing time, for each joint discrete interval of $(pw, T_s, f, \Delta T_{sc})$, pseudoradiance is divided into a number of equal intervals from minimum to maximum possible pseudoradiance. When difference between minimum and maximum pseudoradiances ($\psi$) is small (e.g., discrete intervals for nearly overcast low clouds), only four intervals are used to characterize the variation of $\psi$. When such difference between minimum and maximum $\psi$ is large (e.g., discret intervals for nearly overcast high clouds), twenty intervals are used. In between, twelve intervals are used. Last, MODTRAN5 is used to simulate $I_v(\theta)$ and $F_v$ at each AIRS channel and then $R_v(\theta)$ is obtained according to equation (2).

In summary, discretizing pseudoradiance($\psi$) adds one more dimension to the original four dimensions of CERES-SSF LW ADM ($pw$, $T_s$, $f$, and $\Delta T_{sc}$) and, by doing so, $R_v(\theta)$ can be estimated for each joint discrete intervals of $(pw, T_s, f, \Delta T_{sc}, \psi)$.

3.1.2 Estimating fluxes over frequencies not covered by AIRS

Because the grating spectrometer of AIRS does not cover the entire range of longwave spectrum, measures have to be taken to estimate fluxes over spectral ranges without AIRS observations. The method used here is exactly identical to the one described in the part I [Huang et al., 2008]. In brief, frequency gaps are filled with channels having approximately the same spectral resolutions as the nearest AIRS channels (hereafter, “filled-in” channels). Spectral fluxes over these filled-in channels are
then estimated with a multi-regression scheme based on the principal component analysis. Parameters in the regression scheme are derived based on the profiles used in section 3.1.1 for each given joint discrete interval of \((pw, T_s, f, \Delta T_{sc}, \psi)\). The regression scheme essentially finds the least-square-fit of the projections of spectral fluxes at AIRS channels onto the predefined principal components. A chart summarizing the entire algorithm is shown in Figure 1, which is similar to the Figure 4 in Huang et al. [2008].

3.2 Validations

As in the part I [Huang et al., 2008], the validation is carried out in two parts. The first part is “theoretical validation”, comparing the spectral fluxes derived from the synthetic AIRS spectra to those directly computed from the MODTRAN5, which allows us to assess the entire algorithm without concerning the accuracies in spectroscopy and in the forward model since the MODTRAN5 is deemed as truth through the entire process. The second part uses the algorithm to derive the broadband OLR from the AIRS spectrum and compare it with the collocated CERES OLR, and then characterizing the OLR differences for different combinations of cloud fractions and cloud-surface temperature differences. The second part is more rigorous in the sense that all realistic uncertainties, such as those in spectroscopy, the forward model, and collocation strategies, have been taken into account.

3.2.1 Theoretical validation

We have examined 32 randomly selected discrete intervals for each of following cases: cloud with inversion boundary layer, low clouds, middle clouds, and high clouds.
For each discrete interval, 100 profiles are identified from randomly selected ECMWF ERA-40 6-hourly data (different period from that of the trained dataset used in section 3.1). These profiles are then fed into MODTRAN5 to compute OLRs, spectra fluxes, and the synthetic AIRS spectra. Theoretical validation is then done by examining the OLRs and spectral fluxes directly computed from MODTRAN5 (hereafter, computed OLR or spectral fluxes) and the counterparts estimated from synthetic AIRS spectra by the algorithm described in section 3.1 (hereafter, estimated OLR or spectra fluxes). Presented below are summary of eight discrete intervals that have the largest discrepancies between computed and estimated OLR. The detailed information of the eight discrete intervals is tabulated in Table 2. For the rest 24 discrete intervals that we examined, the OLR difference is within ±5 Wm\(^{-2}\) and the spectral flux difference is also generally smaller than what is discussed below.

Figure 2 shows differences between directly computed OLR and estimated OLR from synthetic AIRS spectra for three different zenith angels. The mean difference is between -3.66 and 1.11 Wm\(^{-2}\) for all discrete intervals and zenith angles shown here. The standard deviation is within 2.94 Wm\(^{-2}\) and maximum difference for any individual case is within ±12.9 Wm\(^{-2}\). For all three zenith angles examined here, the largest differences are always seen in the H2 interval as defined in Table 2. The H2 interval is characterized with large amount precipitable water, large cloud-surface temperature contrast, and very high surface temperature (>305K). Such combinations are not frequently seen in ECMWF ERA-40 data. As a result, only around 200 cases from the training dataset are identified...
for the H2 interval and used to develop the algorithm. Therefore, the large difference here for the H2 interval is at least partially due to the fact that the spectral ADM and regression parameters are derived from a very limited set of training profiles.

Figure 3a shows absolute differences between directly computed spectral fluxes over 10 cm\(^{-1}\) spectral bin and the estimated ones from synthetic nadir-view AIRS spectra while Figure 3b shows the corresponding relative differences. The largest absolute difference (\(\pm 0.025 \text{ Wm}^{-2}/10\text{cm}^{-1}\)) is mostly seen over the 650-800 cm\(^{-1}\) region of the two discrete intervals featured with inversion boundary layer (I1 and I2 intervals); but the corresponding relative difference is indeed small (within 2\%, Figure 3b). The largest relative difference is only about \(\pm 3.6\%\) as shown in Figure 3b, which is mostly seen in the water vapor \(\nu 2\) band (>1300 cm\(^{-1}\)), a band contributing only 2-3\% to the broadband OLR. The number of profiles used to derive the algorithm for the I1 and I2 intervals are indeed significantly less than 1200. Such limited samples in the training dataset could be a reason why both the largest absolute differences and relative differences tend to happen at the I1 and I2 intervals.

Overall theoretical validations suggest the algorithm itself can reliably estimate spectral fluxes at 10 cm\(^{-1}\) spectral bin through the entire longwave spectrum. The maximum relative difference for any given 10 cm\(^{-1}\) spectral bin is within 3.6\% for all discrete intervals that we have examined. These results give us confidence in applying the algorithm to the real AIRS spectra in the next validation step.

### 3.2.2 Comparisons of derived OLR with the CERES OLR


For collocated AIRS and CERES cloudy-sky observations over the tropical oceans in the entire year of 2004, the AIRS spectra are used to estimate spectral fluxes over every 10 cm$^{-1}$ spectral bin. Broadband OLR estimation is merely a summation of such 10 cm$^{-1}$ spectral fluxes (hereafter, OLR derived in this way is referred as OLR$_{AIRS}$). Then OLR$_{AIRS}$ is compared to the collocated OLR from the CERES SSF product (hereafter, OLR$_{CERES}$). The differences of OLR$_{AIRS}$-OLR$_{CERES}$ are then further examined for different cloud fractions as well as different surface-cloud temperature differences.

In total 11.79 millions of collocated AIRS and CERES observations over cloudy tropical oceans have been identified for the entire year of 2004. The histogram of differences between OLR$_{AIRS}$ and OLR$_{CERES}$ is shown in Figure 4a, with a mean difference of 2.15 Wm$^{-2}$ and a standard deviation of 5.51 Wm$^{-2}$. CERES SSF product also contains IR window-channel (8.1-11.8 μm) flux obtained from its narrow-band radiometer over the window region. For comparison, figure 4b shows the histogram of differences between window-channel flux estimated from AIRS spectra and collocated CERES window-channel flux. The mean difference is -0.27 Wm$^{-2}$ with a standard deviation of 2.50 Wm$^{-2}$. Both histograms show Gaussian-like distribution. 91.7% of OLR$_{AIRS}$-OLR$_{CERES}$ differences are within ±10 Wm$^{-2}$ and 99.7% of them within ±27 Wm$^{-2}$.

Though occurrence of large OLR$_{AIRS}$-OLR$_{CERES}$ difference is rare, the minimum and maximum differences of OLR$_{AIRS}$-OLR$_{CERES}$ for cloudy scenes could be as large as -66.5 and 58.7 Wm$^{-2}$, respectively (Figure 4a). In contrast, the largest clear-sky OLR$_{AIRS}$-OLR$_{CERES}$ difference is only around ±10 Wm$^{-2}$ [Huang et al., 2008]. The
CERES footprint is larger than the AIRS footprint (at nadir view, ~20km vs. 13km). Therefore, if cloud distributions within the 20-km CERES footprint vary significantly (i.e. extremely inhomogeneous cloud distribution), cloud properties (cloud fraction and cloud top temperature) observed by CERES can differ from those observed by AIRS. Consequently large bias (either positive or negative) could be introduced for such very inhomogenous cloud scenes when the CERES ADM is directly applied to the collocated AIRS footprint. This is different from the clear-sky scenes because a clear-sky CERES footprint is generally far more homogeneous. To understand the possible impact of such cloud spatial inhomogeneity within a CERES footprint, we sort the AIRS-CERES differences (for both the OLR and the window-channel flux) according to a cloud inhomogeneity index (hereafter denoted as $r_{\text{MODIS}}$) determined from the ratio of the standard deviation-to-mean 1-km MODIS 11\(\mu\)m radiances within CERES footprints. The mean and standard deviation of MODIS radiances within a CERES footprint are provided in the CERES SSF product. The higher $r_{\text{MODIS}}$ is, the more inhomogenous the scene is. If the cloud distribution within a CERES footprint is very inhomogenous, then the cloud amount in the collocated AIRS footprint can be either more or less than the cloud amount of the entire CERES footprint. As a result, the true difference of $\text{OLR}_{\text{AIRS}}-\text{OLR}_{\text{CERES}}$ (or window-channel flux difference) could either be negative or positive. But the amplitude of the difference (e.g., the absolute value of $\text{OLR}_{\text{AIRS}}-\text{OLR}_{\text{CERES}}$) should be sensitive to the degree of inhomogeneity within the CERES field of view. We thus use the absolute value of $\text{OLR}_{\text{AIRS}}-\text{OLR}_{\text{CERES}}$ (or window-channel flux difference) here and study how it
changes with respect to \( r_{\text{MODIS}} \).

Figure 4c shows the mean absolute differences of \( \text{OLR}_{\text{AIRS}}-\text{OLR}_{\text{CERES}} \) (gray stars) and window-channel fluxes (black circles) as a function of \( r_{\text{MODIS}} \). The error bars in figure 4c correspond to \( \pm 1 \) standard deviation and the bin size of \( r_{\text{MODIS}} \) is 0.1 with 10 bins centered from 0.05 to 0.95. All 11.79 millions of collocated AIRS and CERES cloudy observations over the tropical oceans are used for constructing Figure 4c and 4d. As expected, the smaller \( r_{\text{MODIS}} \) corresponds to smaller absolute flux differences for both the OLR and the window channel. Figure 4d shows the histogram of \( r_{\text{MODIS}} \) in logarithmic scale, which indicates a nearly exponential decay of the number of footprints with \( r_{\text{MODIS}} \): 77.1% of the cases have \( r_{\text{MODIS}} \) no more than 0.1 and 99.2% of them have \( r_{\text{MODIS}} \) no more than 0.4. As showed in Figure 4c, the mean absolute OLR difference for the bin \( 0.3 \leq r_{\text{MODIS}} < 0.4 \) is 10.9 Wm\(^{-2}\). Figure 4c and 4d together indicate that the very inhomogenous cloud distributions within the CERES footprint are responsible for the very large \( \text{OLR}_{\text{AIRS}}-\text{OLR}_{\text{CERES}} \) differences shown in Figure 4a, but the frequency of occurrence of such very inhomogeneous scenes is extremely small (0.8% scenes have \( r_{\text{MODIS}} \) larger than 0.4). Such statistics give us further assurance of applying our algorithm to collocated CERES and AIRS observations.

We further examine the \( \text{OLR}_{\text{AIRS}}-\text{OLR}_{\text{CERES}} \) differences for different cloud fractions \( (f) \) as well as different cloud-surface temperature contrast \( (\Delta T_{sc}) \). \( f \) is divided into four bins as defined in Table 1. \( \Delta T_{sc} \) is divided to three bins, approximately representing low clouds, middle clouds, and high clouds, respectively. Table 3 summarizes the mean and
Changes of mean differences from one combination to another are small and more sensitive to $\Delta T_{sc}$ than the cloud fraction. For low clouds and high clouds, the mean differences are clustered around $\sim 2.1$ Wm$^{-2}$. For the middle-cloud categories, the mean differences are $\sim 4-5$ Wm$^{-2}$. Given the prevalence of mixed-phase clouds for the middle-cloud categories, the relatively larger difference for such categories might be due to different treatment of mixed-phase clouds in our algorithm (which is MODTRAN5 default spectral properties for altostratus) and CERES SSF algorithm. Nevertheless, the relative mean differences are 2.2% or even less for middle clouds and $\sim 1\%$ or less for low and high clouds.

Based on above comparisons, we conclude that the OLR produced by our algorithm agrees well with CERES OLR across different cloud types and cloud fractions. The mean OLR difference is $2.15$ Wm$^{-2}$ and the standard deviation is $5.51$ Wm$^{-2}$. Large OLR differences (e.g. beyond $\pm 20$ Wm$^{-2}$) are mainly due to the very inhomogeneous cloud distribution but the occurrence of such cases are rare ($\sim 0.8\%$ when $r_{MODIS}$ is used as indicator of cloud inhomogeneity). Such favorable comparisons give further confidence in using the algorithm to extract spectral fluxes and then band-by-band CRFs.

Detailed study to quantify the sources of $2.15$ Wm$^{-2}$ mean difference between $\text{OLR}_{\text{AIRS}}$ and $\text{OLR}_{\text{CERES}}$ is beyond the scope of this study. Possible leading candidates are difference in absolute radiometric calibration, biases in scene identification, and differences between CERES ADM and the spectral ADM developed here. Both AIRS and
CERES have carefully designed and in-flight validated calibration procedures. Moreover, the difference in absolute radiometric calibration, if any, should be reflected in both clear-sky and cloudy-sky comparisons. The clear-sky $\text{OLR}_{\text{AIRS}} - \text{OLR}_{\text{CERES}}$ difference is only 0.67 W/m$^2$ [Huang et al., 2008]. Therefore, the contribution from calibration is likely at most around this magnitude. Figure 4d suggests the nearly negligible contributions from scene heterogeneity between CERES and AIRS field of view. Furthermore, the very fine discrete intervals of each scene type defined in CERES ADM also help reduce possible biases originated from scene identification. Therefore, we speculate that the largest contributor to the $\text{OLR}_{\text{AIRS}} - \text{OLR}_{\text{CERES}}$ is the subtle differences between CERES broadband ADM and the spectral ADM derived in this study.

4. **Application in GCM evaluation**

The previous section derives band-by-band flux for cloudy-sky observations. Together with band-by-band clear-sky flux derived in Huang et al. [2008], band-by-band CRFs can then be estimated in the same manner as the broadband CRF derived from ERBE or CERES observations. Then they can be compared to counterparts from GCM simulations. We use the GFDL AM2 model as a case study here. The AM2 model is forced with the observed SST and 3-hourly band-by-band CRFs are archived for the year of 2004, which are then further interpolated onto the times and tracks of AIRS&CERES collocated observations. AM2 longwave radiation scheme has eight bands as listed in Table 4 (in practice the H2O rotational band and the v2 vibrational-rotational band are treated together as Band1, making seven bands in total). Both AIRS and CERES
observations happen at fixed local time, around 1:30am and 1:30pm. Therefore, daytime and nighttime CRFs are first computed separately and then the daytime and nighttime averages are equally weighted to obtain the overall average. By doing so, bias due to different number of samplings during daytime and nighttime can be minimized. Note no temporal interpolation is employed here. Thus, the average discussed below is the average of two snapshots on the diurnal cycle separated by 12 hours (for both observation and model), instead of the true average over the entire diurnal cycle as in the CERES level-3 monthly-mean fields. We will focus on the annual means of such band-by-band CRFs as seen from the GFDL AM2 simulations and AIRS&CERES collocated observations.

4.1 Annual-mean CRFs: AIRS&CERES vs. AM2

Figure 5 shows the annual-mean spectral CRF over 10 cm\(^{-1}\) spectral bins as derived from the AIRS&CERES collocated observation in 2004. The center of CO\(_2\) v2 band (~ 650-690 cm\(^{-1}\)) is flat, which is expected since this region is sensitive to the emission in the stratosphere. The ozone infrared band is not saturated through the entire atmosphere and hence can be affected by thermal contrast between surface and clouds.

The annual means of band-by-band CRFs and longwave broadband CRF from AIRS&CERES observations are tabulated in Table 4. The fractional contribution of each band to the longwave broadband CRF is also listed. Counterparts from the AM2 simulation are listed in a separate column in Table 4. For comparison, the corresponding tropical means of band-by-band clear-sky fluxes and their fractional contributions to
clear-sky OLR are listed in the last column of Table 4. The fractional contribution of each
band to the broadband CRF is generally not proportional to its fractional contribution to
the clear-sky OLR. For example, the H$_2$O pure rotational band contributes about 38.8% to
the clear-sky OLR but only ~19% to the longwave CRF. One window band
(1070–1200 cm$^{-1}$), on the other hand, contributes ~10% to the clear-sky OLR but ~17% to
the broadband CRF. Such disproportionality is due to two facts. First, cloud top
temperature generally is colder than the surface temperature and, according to the Wien’s
displacement law, the maximum emission shifts towards lower wavenumber. Second,
spectral dependences of emission and absorption of clouds further contribute to such
disproportional change of contributions to clear-sky OLR versus those to longwave CRF.

Comparing the observation and simulation columns in Table 4, AIRS&CERES
observation and the AM2 model generally agree with each other on both absolute
magnitude of the CRF and the fractional contribution of each band. The spatial
distributions of observed and simulated longwave broadband CRF (the upper panels of
Figure 6) are largely consistent with each other. The largest contribution to broadband
longwave CRF comes from the water vapor bands, consisting of ~19.25% of the total
longwave CRF. As far as the spatial distribution for the water–vapor-band contributions
to the longwave CRF is concerned (the middle panels of Figure 6), observation and
simulation agrees on vast area of the tropics, with the AIRS&CERES observations being
slightly higher than the AM2 model. The largest discrepancies between AIRS&CERES
and AM2 exist in the regions with frequent occurrences of marine stratus, where the
fractional contribution in AM2 (~15%) is much higher than that in AIRS&CERES (~5% or less). Therefore, for the water vapor bands, the seemingly agreement on the tropical-averaged fractional contribution between observation and simulation (the third row in Table 4) is indeed due to compensating effect from different geographical regions. Table 4 also shows that the contribution from 800-900 cm\(^{-1}\), a window band, to the longwave broadband CRF is only slightly smaller (~18.75%, Table 4) than that from the water vapor rotational band, even the clear-sky flux over this band is less than one-third of the water vapor rotational band. Relatively large discrepancy can be seen in another window band (1070-1200 cm\(^{-1}\)): observed fractional contribution is 15.7% while the simulated is 18.9%. Spatial maps (the lower panels of Figure 6) of this band indicate that the simulated contribution of this band is higher than the observed all over the tropical oceans, especially regions featured with frequent coverage of marine stratus. The contrasts in fractional contribution here clearly show the discrepancies between observation and model that cannot be revealed by the broadband CRF comparison alone.

### 4.2 An idealized model for band-by-band CRF

An idealized model with one layer of cloud is used here to further interpret the band-by-band CRF results. Sketch of the model is shown in Figure 7a. The fraction of cloudy-sky (cloud fraction) is \(f\). Cloud is opaque and MODTRAN5 default cloud spectral features are used in computing fluxes. Typical tropical sounding profiles of temperature, water vapor, trace gases from *McClatchy et al.* [1972] are used in the calculation. \(F_{\text{clr}}(\Delta \nu)\) and \(F_{\text{clld}}(\Delta \nu)\) are the clear-sky and cloudy-sky fluxes of a band with a bandwidth of \(\Delta \nu\),
respectively. Then the CRF of this band can be written as

$$\text{CRF}(\Delta \nu) = f[F_{\text{clr}}(\Delta \nu) - F_{\text{clld}}(\Delta \nu)]$$  \hspace{1cm} (3)$$

The longwave broadband CRF is

$$\text{CRF}_{\text{LW}} = f[F_{\text{clr\_LW}} - F_{\text{clld\_LW}}]$$  \hspace{1cm} (4)$$

where the subscript of LW denotes the longwave broadband quantity (i.e. OLR). The fractional contribution of this band to the CRF_{LW} can then be written as

$$r(\Delta \nu) = \frac{\text{CRF}(\Delta \nu)}{\text{CRF}_{\text{LW}}} = \frac{[F_{\text{clr}}(\Delta \nu) - F_{\text{clld}}(\Delta \nu)]}{[F_{\text{clr\_LW}} - F_{\text{clld\_LW}}]}$$  \hspace{1cm} (5)$$

While absolute CRF depends on cloud fraction and cloud top height, \(r(\Delta \nu)\) here is not dependent on cloud fraction. For this model, the opaque cloud implies that the outgoing flux over the cloudy-sky portion is largely determined by emission from cloud top. Therefore, it can be expected that \(r(\Delta \nu)\) would vary with the cloud top height. Figure 7b shows such variations of \(r(\Delta \nu)\) for all bands listed in Table 4 when the cloud top height changes from 2km to 15km. When the cloud top is low, the maximum contributions are from the window bands since the water vapor bands are mostly sensitive to mid- and upper-troposphere and vary little from the clear-sky portion to the cloudy-sky portion. As the cloud top height gradually increases, contributions from the window bands become smaller and those from the water vapor bands become larger. This is because the peak of cloud emission shifts towards lower wavenumber as cloud top temperature is colder. If the model is used to fit the fractional contributions of AIRS&CERES observations, the best fit is achieved when cloud top height is at 9.3km (Figure 7c). Figure 7c shows that this highly idealized model can capture the major features of AIRS&CERES band-by-band
fractional contribution. The best fit for the AM2 simulation is a cloud top height at 9.5km (not shown here). Once the cloud top height $z_{\text{cld}}$ is determined, the cloud fraction can be obtained by

$$f = \text{CRF}_{\text{LW}} / [\text{F}_{\text{clr\_LW}} - \text{F}_{\text{cld\_LW}}(z_{\text{cld}})]$$

(6)

where $\text{F}_{\text{cld\_LW}}(z_{\text{cld}})$ is the longwave broadband flux for overcast sky with cloud topping at $z_{\text{cld}}$, and CRF$_{\text{LW}}$ is the AIRS&CERES (or AM2) longwave broadband CRF. This would yield a cloud fraction of 24.8% for the AIRS&CERES observation and 25.4% for the AM2 simulation.

The merit of fractional contribution of each band is illustrated by this conceptual model. While the broadband CRF contains two independent macroscopic cloud variables, i.e., cloud fraction and cloud top height, the fractional contributions of individual bands can effectively constrain the cloud top height since it is largely insensitive to the cloud fraction. Cloud fraction can then be estimated once the cloud top height is determined.

5. Conclusion

An algorithm is presented here for deriving spectral flux at 10cm$^{-1}$ spectral interval through the entire longwave spectrum range from collocated AIRS and CERES cloudy-sky observations over the tropical oceans. Its main methodology is identical to the one used in Huang et al. [2008]. The algorithm adopts scene type classifications in the CERES-SSF algorithm and builds corresponding spectral ADMs, then employs a multivariate linear regression scheme to estimate fluxes over frequencies not covered by the AIRS instrument. The theoretical validation compares estimated spectral flux from
synthetic AIRS data with directly computed spectral flux, indicating maximum fractional
difference within ±3.6%. When comparing OLR derived from real AIRS spectra with the
collocated CERES OLR, mean difference is 2.15Wm⁻² with a standard deviation of
5.51Wm⁻². The large differences (e.g. beyond ±27Wm⁻²) is rare and mostly due to very
non-uniform cloud distribution within the collocated CERES footprints, as suggested by
the relation between absolute OLRₐᵢᵦₛ-OLRₖₑᵦᵦₑₛ differences and rₑᵦₑᵦᵦₑᵦᵦᵦₑᵦᵦₛ, an indicator
based on MODIS imagery radiance to describe the degree of scene inhomogeneity within
the CERES footprint. The statistics of OLRₐᵦᵦₑᵦᵦₑᵦᵦₑₛ-OLRₖₑᵦᵦₑᵦᵦₑₛ differences are similar for
different combinations of cloud fractions and cloud types. These facts indicate that the
algorithm performs consistently well for all types of cloudy conditions and has no
significant bias towards any particular types of clouds.

Based on the spectral fluxes derived for cloudy-sky and clear-sky observations,
band-by-band CRF is derived for the entire year of 2004. Such band-by-band CRF is then
compared to the counterpart from a GCM simulation (the GFDL AM2 model) forced by
the observed SST. An idealized model with one layer of cloud is used to illustrate the
advantage of band-by-band CRF. The fractional contribution of each band to the LW
broadband CRF is insensitive to the cloud fraction but sensitive to cloud top height
(equivalently, cloud top temperature). Once the cloud top temperature is estimated from
the fractional contributions of different bands, cloud fraction can then be determined by
the ratio of the actual broadband CRF to the broadband CRF of overcast situation. As far
as the tropical-mean band-by-band CRFs are concerned, the AIRS&CERES observation
and AM2 simulation generally agree with each other for both the absolute magnitude and fractional contribution of each band. The largest difference (~1 Wm$^{-2}$) is seen in one of the window bands (1070-1200 cm$^{-1}$). Spatial maps of fractional contribution from the water vapor bands and the window bands both indicate large discrepancies in regions with frequent occurrences of low clouds.

To our knowledge, this is the first time that band-by-band CRFs over the entire longwave spectral range are studied from the combined point of views of satellite observations and GCM modelings. Band-by-band CRFs and fluxes bring additional informative dimensions into the GCM evaluation. To a large extent, diagnostic study using such quantities excludes the nuisance compensating biases from different bands, an issue unavoidable when only broadband quantities are examined. As cloud feedback remains one of key questions in advancing GCM modeling, there is pressing need to decipher modeled biases in CRF and in cloud feedbacks from multitude points of view.

Given the intrinsic complexity of cloud feedback mechanism and its intricate connections with radiation, dynamics, and moist processes, orchestrated studies involving different aspects of cloud observations would be required to understand such biases [Stephens 2005]. The feasibility of obtaining band-by-band fluxes and, by extension, band-by-band CRFs from observations, as well as their merits in the GCM evaluation, are showed here and in Huang et al. [2008] by using currently available AIRS and CERES observations and the GFDL AM2 model. Such band-by-band quantities are also potentially obtainable from other ongoing or planning hyperspectral measurements (e.g. IASI, CrIS, and
CLARREO). Thus, practically band-by-band fluxes and CRFs can play an important role in the orchestrated studies towards a better understanding and simulation of cloud feedback.

Acknowledgements

We are greatly indebted to Dr. V. Ramaswamy and NOAA GFDL for the generosity of providing computing resources for the AM2 simulation and relevant data analysis. The AIRS data were obtained from NASA GSFC DAAC and the CERES data from NASA Langley DAAC. The ECMWF ERA-40 reanalysis data were obtained from http://data.ecmwf.int/data/d/era40_daily/. One of the authors, X. Huang, thanks Drs. L. Strow, G. Aumann, T. Pagano, B. Kahn, S. Souze-Machado, S.Y. Lee, and Z. Luo for valuable discussions and helps on understanding the AIRS data. This research is supported partly by NSF AGS CLD program under grant NSF ATM 0755310 and NASA MAP project under grant NNX09AJ46G awarded to the University of Michigan.
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Xu, K. M. (2009), Evaluation of Cloud Physical Properties of ECMWF Analysis and Re-Analysis (ERA) against CERES Tropical Deep Convective Cloud Object

Table Caption

Table1. Discrete intervals of precipitable water ($pw$), cloud fraction ($f$), surface-cloud temperature difference ($\Delta T_{sc}$), and surface skin temperature ($Ts$) used by CERES longwave ADMs under cloudy conditions over the ocean, land, and desert (adapted from Table 4 in Loeb et al. [2005]).

<table>
<thead>
<tr>
<th>pw (cm)</th>
<th>f</th>
<th>$\Delta T_{sc}$ (K)</th>
<th>$Ts$ (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1</td>
<td>0.001-0.5</td>
<td>&lt;15;</td>
<td>&lt;275;</td>
</tr>
<tr>
<td>1-3</td>
<td>0.5-0.75</td>
<td>-15 to 85 every 5k;</td>
<td>&gt;275 to 320 every 5k;</td>
</tr>
<tr>
<td>3-5</td>
<td>0.75-0.999</td>
<td>85</td>
<td>320</td>
</tr>
<tr>
<td>&gt;5</td>
<td>0.999-1.0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table2. Eight discrete intervals used in the theoretical validation (subsection 3.2.1 as well as Figure2 and Figure3). Symbol definitions are same as in Table1. I, L, M, and H refer to inverse-layer, low-cloud, middle-cloud, and high-cloud, respectively.

<table>
<thead>
<tr>
<th></th>
<th>pw (cm)</th>
<th>f</th>
<th>$\Delta T_{sc}$ (K)</th>
<th>$Ts$ (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I1</td>
<td>0-1</td>
<td>0.001-0.5</td>
<td>[-10K, -5K]</td>
<td>[290K, 295K]</td>
</tr>
<tr>
<td>I2</td>
<td>0-1</td>
<td>0.001-0.5</td>
<td>[-5K, 0K]</td>
<td>[290K, 295K]</td>
</tr>
<tr>
<td>L1</td>
<td>&gt;5</td>
<td>0.999-1.0</td>
<td>[5K, 10K]</td>
<td>[300K, 305K]</td>
</tr>
<tr>
<td>L2</td>
<td>&gt;5</td>
<td>0.999-1.0</td>
<td>[10K, 15K]</td>
<td>[300K, 305K]</td>
</tr>
<tr>
<td>M1</td>
<td>&gt;5</td>
<td>0.999-1.0</td>
<td>[25K, 30K]</td>
<td>[300K, 305K]</td>
</tr>
<tr>
<td>M2</td>
<td>&gt;5</td>
<td>0.999-1.0</td>
<td>[25K, 30K]</td>
<td>[300K, 305K]</td>
</tr>
<tr>
<td>H1</td>
<td>&gt;5</td>
<td>0.999-1.0</td>
<td>[55K, 60K]</td>
<td>[300K, 305K]</td>
</tr>
<tr>
<td>H2</td>
<td>&gt;5</td>
<td>0.999-1.0</td>
<td>[85K, 90K]</td>
<td>[300K, 305K]</td>
</tr>
</tbody>
</table>
Table 3. Differences between OLR estimated from AIRS spectra (OLR\textsubscript{AIRS}) and the collocated CERES OLR (OLR\textsubscript{CERES}) for different combinations of cloud fractions (f) and cloud-surface temperature difference (ΔT\textsubscript{sc}). Mean ± standard deviation of the difference are given for each combination. The fractional mean difference, i.e. (OLR\textsubscript{AIRS}-OLR\textsubscript{CERES})/OLR\textsubscript{CERES}, is given in parentheses.

<table>
<thead>
<tr>
<th>F</th>
<th>ΔT\textsubscript{sc}</th>
<th>&lt;15K</th>
<th>15K-40K</th>
<th>&gt;40K</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.001-0.5</td>
<td>1.98±2.04Wm\textsuperscript{2}</td>
<td>3.93±3.53Wm\textsuperscript{2}</td>
<td>2.91±4.75Wm\textsuperscript{2}</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.6%)</td>
<td>(1.4%)</td>
<td>(1.1%)</td>
<td></td>
</tr>
<tr>
<td>0.5-0.75</td>
<td>2.32±3.36Wm\textsuperscript{2}</td>
<td>4.51±6.18Wm\textsuperscript{2}</td>
<td>2.18±8.80Wm\textsuperscript{2}</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.8%)</td>
<td>(1.7%)</td>
<td>(0.9%)</td>
<td></td>
</tr>
<tr>
<td>0.75-0.999</td>
<td>2.02±3.15Wm\textsuperscript{2}</td>
<td>4.10±6.89Wm\textsuperscript{2}</td>
<td>-0.12±10.40Wm\textsuperscript{2}</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.74%)</td>
<td>(1.7%)</td>
<td>(-0.05%)</td>
<td></td>
</tr>
<tr>
<td>0.999-1.0</td>
<td>2.00±2.49Wm\textsuperscript{2}</td>
<td>5.08±5.70Wm\textsuperscript{2}</td>
<td>1.58±7.99Wm\textsuperscript{2}</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.74%)</td>
<td>(2.2%)</td>
<td>(0.9%)</td>
<td></td>
</tr>
</tbody>
</table>
Table 4. Annual means of band-by-band CRFs over the tropical oceans as derived from the collocated AIRS and CERES observations in 2004 and as simulated by the AM2 model forced by the observed SST in 2004. The numbers in parentheses are fractional contribution to the longwave broadband CRF. For contrast, the clear-sky OLR and band-by-band fluxes of AM2 tropical annual means are given in the last column, with numbers in parentheses being the fractional contribution to the clear-sky OLR.

<table>
<thead>
<tr>
<th></th>
<th>AIRS&amp;CERES observed CRF (in Wm$^{-2}$)</th>
<th>AM2 simulated CRF (in Wm$^{-2}$)</th>
<th>AM2 clear-sky flux (in Wm$^{-2}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LW broadband</td>
<td>27.45 (100%)</td>
<td>28.13 (100%)</td>
<td>290.88 (100%)</td>
</tr>
<tr>
<td>0-560 cm$^{-1}$; &gt;1400 cm$^{-1}$</td>
<td>5.36 (19.5%)</td>
<td>5.33 (19.0%)</td>
<td>112.98 (38.8%)</td>
</tr>
<tr>
<td>560-800 cm$^{-1}$</td>
<td>4.18 (15.2%)</td>
<td>3.74 (13.3%)</td>
<td>57.52 (19.8%)</td>
</tr>
<tr>
<td>800-900 cm$^{-1}$</td>
<td>5.11 (18.6%)</td>
<td>5.32 (18.9%)</td>
<td>35.39 (12.2%)</td>
</tr>
<tr>
<td>900-990 cm$^{-1}$</td>
<td>4.24 (15.5%)</td>
<td>4.71 (16.7%)</td>
<td>28.07 (9.7%)</td>
</tr>
<tr>
<td>990-1070 cm$^{-1}$</td>
<td>2.02 (7.0%)</td>
<td>1.68 (6.0%)</td>
<td>12.92 (4.4%)</td>
</tr>
<tr>
<td>1070-1200 cm$^{-1}$</td>
<td>4.31 (15.7%)</td>
<td>5.33 (18.9%)</td>
<td>28.59 (9.8%)</td>
</tr>
<tr>
<td>1200-1400 cm$^{-1}$</td>
<td>2.22 (8.1%)</td>
<td>2.01 (7.2%)</td>
<td>15.43 (5.3%)</td>
</tr>
</tbody>
</table>
Figure Captions

Figure 1. Flow-chart illustration of the algorithm for deriving spectral fluxes from the collocated AIRS and CERES measurements. Notations are the same as those defined in the section 3 of part I of this study [Huang et al., 2008].

Figure 2. Upper panel: Differences between the OLR predicted from the synthetic nadir-view AIRS spectra and directly computed OLR from MODTRAN™-5 for eight discrete intervals of CERES cloudy scenes listed in Table 2. The diamond is the mean difference, the error bar shows the mean ± standard deviation, the dashed lines are the maximum and minimum differences. (b) Same as (a) except a zenith angle of 18°. (c) Same as (a) except a zenith angle of 45°.

Figure 3. (a) The mean differences between the predicted TOA spectra fluxes based on synthetic AIRS spectra and the directly computed TOA spectral fluxes from MODTRAN™-5 for each ADM discrete interval. The spectral flux is computed for every 10 cm⁻¹ bin from 10 to 2000 cm⁻¹. Ordinate represents the 8 discrete intervals listed in Table 2. The unit of the mean difference is W per m² per 10 cm⁻¹. (b) Same as (a) but for the fractional difference.

Figure 4. (a) The histogram of differences between OLR estimated from real AIRS spectra and the collocated CERES OLR (OLR_{AIRS}−OLR_{CERES}) over the cloudy tropical oceans in the entire year of 2004. 11.79-million collocated observations are analyzed. Mean and standard deviation of the differences are labeled on the plot. (b) Same as (a)
except for the difference between the window-channel (8.1-11.8μm) fluxes estimated from the AIRS spectra and derived in CERES SSF product (WN\textsubscript{AIRS}-WN\textsubscript{CERES}). (c) The absolute differences of OLR\textsubscript{AIRS}-OLR\textsubscript{CERES} (or WN\textsubscript{AIRS}-WN\textsubscript{CERES}) as a function of r\textsubscript{MODIS}, the ratio of standard deviation-to-mean 1-km MODIS 11μm imagery radiances within the entire CERES field of view. The bin size of r\textsubscript{MODIS} is 0.1 with ten bins from 0.05 to 0.95. The mean OLR differences are in gray stars and the mean window-channel flux differences in black circles. The error bars represents ±1 standard deviation. (d) The histogram of r\textsubscript{MODIS}. Note the ordinate in logarithm scale. Same bin sizes and bin centers as in (c) are used.

Figure 5. The annual-mean spectral CRF at 10cm\textsuperscript{-1} spectral bin, derived from the collocated AIRS\&CERES observations over the tropical oceans for the entire year of 2004. Two vertical dash lines indicate the minimum and maximum frequencies of the AIRS spectra used in this analysis.

Figure 6. Upper panels: The annual-mean longwave broadband CRF from the AIRS\&CERES collocated observations (left side) and from the AM2 simulation (right side). Middle panels: The fractional contribution of water vapor rotational band and vibrational ν2 band to the annual-mean longwave CRF. Lower panels: Same as the middle ones except for 1070-1200cm\textsuperscript{-1}, a window band.

Figure 7. (a) Sketch of the idealized model used in section 4.2. (b) Contours of the fractional contribution of each band to the longwave broadband CRF as the cloud top
height changes from 2km to 15km in the idealized model. Band1-7 refers to the bands defined in Table 4 (the bands used in the GFDL AM2 radiation scheme). (c) The fractional contribution of each band to the longwave CRF. Solid line with diamonds is the AIRS&CERES annual-mean results as listed in Table 4. Dash line is result from the idealized model with an optically thick cloud topping at 9.3km, the best fit to the AIRS&CERES curve.
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