Aqua AIRS Huang Spectral OLR Algorithm
Theoretical Basis Document

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AIRS Data Version 6.1

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# Document History

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<tr>
<td>2020-01-02</td>
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Remarks: This ATBD is based on a series of peer-review publications from Huang’s group at the University of Michigan since 2008, i.e. Huang et al. (2008), Huang et al. (2010), Chen et al., (2013), Huang et al. (2014), Chen et al. (2016), and Huang et al. (2019). All materials presented here can be found in aforementioned articles.
1.0 Introduction

1.1 Purpose

This algorithm theoretical basis document (ATBD) describes the algorithm used to derive the Aqua AIRS Huang Spectral OLR product from the collocated AIRS and CERES data. The product is included in the AIRS Level 3 (L3) product. Specifically, this document describes the data, forward modeling tool and algorithm details, validation results, and published applications of using such products in climate research.

1.2 Abbreviations and Acronyms

<table>
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<th>Abbreviation</th>
<th>Description</th>
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<tr>
<td>ADM</td>
<td>angular distribution model</td>
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<tr>
<td>AIRS</td>
<td>Atmospheric Infrared Sounder</td>
</tr>
<tr>
<td>ASTER</td>
<td>Advanced Spaceborne Thermal Emission Reflection Radiometer</td>
</tr>
<tr>
<td>ATBD</td>
<td>algorithm theoretical basis document</td>
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<tr>
<td>CA</td>
<td>cloud amount</td>
</tr>
<tr>
<td>CALIPSO</td>
<td>Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations</td>
</tr>
<tr>
<td>CanAM4</td>
<td>Canadian Fourth Generation Atmospheric Global Climate Model</td>
</tr>
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<td>CCCma</td>
<td>Canadian Centre for Climate Modeling and Analysis</td>
</tr>
<tr>
<td>CERES</td>
<td>Clouds and the Earth’s Radiant Energy System</td>
</tr>
<tr>
<td>CRE</td>
<td>cloud radiative effect</td>
</tr>
<tr>
<td>CTH</td>
<td>cloud top height</td>
</tr>
<tr>
<td>DOE</td>
<td>Department of Energy</td>
</tr>
<tr>
<td>ECMWF</td>
<td>European Centre for Medium-Range Weather Forecasts</td>
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<tr>
<td>EOF</td>
<td>Empirical Orthogonal Function</td>
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<tr>
<td>FM</td>
<td>flight model</td>
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<tr>
<td>GCM</td>
<td>general circulation model</td>
</tr>
<tr>
<td>GEOS-5</td>
<td>Goddard Earth Observing System, Version 5</td>
</tr>
<tr>
<td>GFDF AM2</td>
<td>Geophysical Fluid Dynamics Laboratory, atmospheric model, version 2</td>
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<tr>
<td>HITRAN</td>
<td>high-resolution transmission molecular absorption database</td>
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<tr>
<td>IFOV</td>
<td>instrument field of view</td>
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<tr>
<td>IGBP</td>
<td>International Geosphere Biosphere Programme</td>
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<tr>
<td>ITCZ</td>
<td>Intertropical Convergence Zone</td>
</tr>
<tr>
<td>LBLRTM</td>
<td>Line-By-Line Radiative Transfer Model</td>
</tr>
<tr>
<td>LW</td>
<td>longwave</td>
</tr>
<tr>
<td>MODTRAN</td>
<td>MODerate resolution atmospheric TRANsmission</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
</tr>
<tr>
<td>NCEP</td>
<td>National Centers for Environmental Prediction</td>
</tr>
<tr>
<td>OLR</td>
<td>outgoing longwave radiation</td>
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<tr>
<td>PS</td>
<td>permanent snow</td>
</tr>
<tr>
<td>SPCZ</td>
<td>Southern Pacific Convergence Zone</td>
</tr>
<tr>
<td>SRF</td>
<td>single scanner footprint</td>
</tr>
<tr>
<td>SST</td>
<td>sea surface temperature</td>
</tr>
<tr>
<td>SW</td>
<td>shortwave</td>
</tr>
<tr>
<td>TOA</td>
<td>top of atmosphere</td>
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2.0 Data Sets and Forward Modeling Tool

The AIRS Huang Spectral OLRs are derived from AIRS radiances based on spectral ADMs for different scene types as defined in the CERES algorithm. Spectral ADMs were built offline using a forward radiative transfer model (MODTRAN5) and ECMWF reanalysis 6-hourly profiles. The scene type, which is also sometimes referred to as “discrete interval” by the CERES SSF algorithms, were obtained from the CERES SSF data products for all collocated footprints. Such scene types have been derived from auxiliary observations and data set fused into the CERES SSF algorithm, such as MODIS, SSM/I, and GEOS operational analysis. Please note the CERES broadband OLR have never been used in the entire derivations, but used for validations.

2.1 CERES

The NASA Aqua spacecraft carries two identical CERES instruments (FM3 and FM4) [Parkinson, 2003]. Aqua is on a Sun-synchronous orbit 705 km above the surface. The IFOV of CERES is about 1.63 degrees, corresponding to a 20 km nadir-view footprint on the surface. At any given time, one CERES instrument is placed in a cross-track scanning mode and the other in either a rotating azimuth scanning or a programmable azimuth plane mode. Given that AIRS is operating in a cross-track scan mode, only CERES observations from the cross-track scanning mode are used in this study. The CERES instruments measure filtered radiances in the shortwave (SW, 0.3–5μm), total (0.3–200μm), and window (WN, 8–12μm) regions. The filtered radiances are then converted to unfiltered reflected solar, unfiltered LW and WN radiances [Loeb et al., 2001]. Corresponding fluxes are derived based on these unfiltered radiances and corresponding ADMs [Loeb et al., 2003; Loeb et al., 2005].

2.2 AIRS

AIRS is an infrared grating array spectrometer aboard Aqua [Aumann et al., 2003]. It records spectra at 2378 channels across three bands (3.74–4.61μm, 6.20–8.22μm, 8.8-15.4μm) with a resolving power (λ/dλ) of 1200. AIRS scans from -49°to 49°with an IFOV of 1.1 degrees, corresponding to a nadir-view footprint of 13.5 km on the surface. The in-flight calibrations show a radiometric accuracy of <0.3 K for a 250 K brightness temperature target [Pagano et al., 2003] and a spectral accuracy of <0.01Δν (here Δν is the full width at half maximum of each channel) [Gaiser et al., 2003]. AIRS collects ~2.9 million spectra per day and global coverage can be obtained in the course of two days. It provides an unprecedented data source of the outgoing thermal IR spectra with excellent calibration and good global coverage. The radiometric stability of AIRS has been proven excellent with an upper bound of 2~3 mk/yr [Aumann et al., 2019].

We used version 5 of the AIRS Level-1B product. Among the 2378 AIRS channels, only those recommended by the AIRS team for Level-2 retrieval purposes are used. AIRS radiances from the 3.74–4.61μm (2169–2673 cm⁻¹) band are not used and the spectral fluxes are derived only for 10–
2000 cm\(^{-1}\). In addition, we screened the data with a strict quality-control procedure to exclude possible bad spectra, as described in the work of Huang and Yung [2005].

2.3 AIRS and CERES Collocation Strategy

Figure 2.3.1 shows part of AIRS and CERES FM4 (in cross-track scanning mode) footprints as sampled from 0106:15 to 0106:45 UTC on 1 January 2005. For each cross-track scanning, AIRS records 90 spectra with scan angle between ±49° while CERES processes the same number of measurements with viewing zenith angles no more than 65.8°. At nadir view, the area of an AIRS footprint is about 45% of that of a CERES footprint. As a result, many AIRS footprints are either completely or largely overlapped within corresponding CERES footprints. Such overlapped measurements, a subset of both AIRS and CERES data, can still render meaningful gridded regional and global products. For collocated AIRS and CERES footprints, the scene type information of the CERES footprint and relevant auxiliary information stored in CERES SSF products can be largely applied to the AIRS pixel. Therefore, such a collocation greatly facilitates the conversion from the AIRS radiances to spectral fluxes, leveraging on the scene type information from the collocated CERES FOV. The collocation criteria adopted in this study are (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 (Δairs-ceres) is less than 3 km. The second criterion ensures that the major portion of AIRS footprint is within the collocated CERES footprint even for a large scan angle. For example, at a scan angle of 45° and Δairs-ceres = 3 km, an AIRS footprint still has at least a 50% overlapping with the collocated CERES footprint. In practice, we only use AIRS data with scan angles within ±45°.

![Figure 2.3.1. The surface footprints of AIRS (solid gray circles) and CERES (open black circles) as observed from about 0106:15 to 0106:45 UTC on 1 January 2005. This is adopted from Figure 1 in Huang et al. [2008].](image)

2.4 ECMWF Reanalysis

During the time period of the algorithm development, ECMWF reanalysis has been upgraded. ERA-40 (covering 1957-2002) [Uppala et al. 2005] is firstly used to build ADMs over ocean surface, then ERA-Interim (covering 1989-present) [Uppala et al. 2008] was used to build ADMs for the other surfaces. These two ECMWF reanalysis are the generations after the ERA-15 (covering 1979-1993) [Gibson et al. 1999]. Primarily we used the 6-hourly profiles of temperature,
humidity, as well as surface skin temperature and surface pressure from such reanalysis data sets. Cloud parameters are specified when building cloudy-sky ADMs.

2.5 Forward Radiative Transfer Model

In order to construct ADMs suitable for the AIRS and estimate spectral fluxes at frequencies not covered by the AIRS instrument, a forward radiative transfer model is needed. We use MODTRAN™-5 version 2 revision11 (hereafter, MODTRAN5) for this purpose. MODTRAN™-5 was collaboratively developed by Air Force Research Laboratory and Spectral Sciences Inc. [Berk et al., 2005]. Mod5v2r11 is based on HITRAN2K line compilation with updates through 2004 [Rothman et al., 2005; Rothman et al., 1998]. Compared to the previous versions of MODTRAN band model [Berk et al., 1998; Bernstein et al., 1996], MODTRAN5 inherits the flexibility in handling clouds and significantly improves the spectral resolution to as fine as 0.1 cm\(^{-1}\). Comparisons between this model and line-by-line radiative transfer model, LBLRTM [Clough and Iacono, 1995; Clough et al., 2005], have shown agreement up to a few percent or better in the thermal IR transmittances and radiances [Anderson et al., 2006]. These features make MODTRAN5 well suited for simulating AIRS radiances [Anderson et al., 2006; Feldman et al., 2006]. In this study, synthetic AIRS spectrum is done by convolving the MODTRAN5 output at 0.1 cm\(^{-1}\) resolution with the spectral response functions of individual AIRS channels [Strow et al., 2003; Strow et al., 2006]. Synthetic spectral fluxes are computed by a 3-point Gaussian quadrature [Clough and Iacono, 1995].

3.0 Algorithm

There are three steps in the algorithm: (1) constructing ADMs, \(R_v(\theta)\), for all applicable AIRS channels and mean synthetic spectral flux \(\tilde{F}_{v_\text{AIRS}}\) for each scene type and for each VZA over the entire LW spectrum, which includes \(\tilde{F}_{\text{AIRS}}\) and \(\tilde{F}_{\text{non-AIRS}}\), (2) estimating the spectral flux at each AIRS channel \(F_{\text{AIRS}}\), and (3) estimating the spectral fluxes at frequencies not covered by the AIRS instrument \(F_{\text{non-AIRS}}\).

Figure 3.0.1 Flowchart illustration of the algorithm for deriving spectral fluxes from the collocated AIRS and CERES measurements. Items in red box are not needed for clear-sky algorithm. This is adapted from Figure 1 in Huang et al. [2010].
3.1 Spectrally Dependent ADMs

An angular distribution model is needed to covert directional radiance measurement to flux. The central quantity in such conversion is the anisotropic factor, which is defined as

\[ R_v(\theta) = \frac{\pi I_v(\theta)}{F_v} \]  

(3.1.1)

where \( I_v(\theta) \) is the upwelling radiance intensity at TOA for frequency \( \nu \) and viewing zenith angle \( \theta \). \( F_v \) is the corresponding upwelling flux. Compared to the broadband anisotropic factor used in CERES ADMs, here \( R \) is not only a function of \( \theta \) but a function of \( \nu \).

The spectral ADM consists of a set of pre-determined look-up tables of \( R_v(\theta) \) for each scene type, each channel and each viewing zenith angle, so it can be used to derive the flux based on (3.1.1) using the AIRS-measured \( I_v(\theta) \). The definitions of scene types for clear sky (Table 3.1.1), cloudy sky (Table 3.1.2), and snow surface (Table 3.1.3) are different.

Table 3.1.1. Definition of clear-sky scene types over ocean, land and desert. Adapted from Table 3 of Loeb et al. [2005]. Each scene type is defined with respect different range of \( p_w \), \( \Delta T \), and \( T_s \), which was referred to as “discrete interval” in Loeb et al. [2005].

<table>
<thead>
<tr>
<th>Precipitable water ((p_w; \text{cm}))</th>
<th>lapse rate ((\Delta T; \text{K}))</th>
<th>surface skin temperature ((T_s; \text{K}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1</td>
<td>&lt;15</td>
<td>&lt;270</td>
</tr>
<tr>
<td>1-3</td>
<td>15-30</td>
<td>270-290</td>
</tr>
<tr>
<td>3-5</td>
<td>30-45</td>
<td>290-310</td>
</tr>
<tr>
<td>&gt;5</td>
<td>&gt;45</td>
<td>&gt;330</td>
</tr>
</tbody>
</table>

Table 3.1.2. Definition of cloudy-sky scene types over ocean, land and desert. Adapted from Table 4 of Loeb et al. [2005].

<table>
<thead>
<tr>
<th>Precipitable water ((p_w; \text{cm}))</th>
<th>cloud fraction ((f))</th>
<th>Surface-cloud temperature difference ((\Delta T_{sc}; \text{K}))</th>
<th>surface skin temperature ((T_s; \text{K}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1</td>
<td>0.001-0.5</td>
<td>&lt;15; 15 to 85 every 5K; &gt;85</td>
<td>&lt;275; 275 to 320 every 5K; &gt;320</td>
</tr>
<tr>
<td>1-3</td>
<td>0.5-0.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-5</td>
<td>0.75-0.999</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;5</td>
<td>0.999-1.0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.1.3. Definition of scene types over permanent snow (PS), fresh snow and sea ice. Adapted from Table 5 of Loeb et al. [2005].

<table>
<thead>
<tr>
<th>Clear fraction ((f_{clr})</th>
<th>surface skin temperature ((T_s; \text{K}))</th>
<th>Surface-cloud temperature difference ((\Delta T_{sc}; \text{K}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.999 &lt; ( f_{clr} \leq 1.000 )</td>
<td>&lt;250 (for fresh snow, sea ice and PS daytime)</td>
<td>&lt;20</td>
</tr>
<tr>
<td>0.750 &lt; ( f_{clr} \leq 0.999 )</td>
<td>&lt;240 (PS, nighttime)</td>
<td></td>
</tr>
<tr>
<td>0.500 &lt; ( f_{clr} \leq 0.750 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.250 &lt; ( f_{clr} \leq 0.500 )</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
To construct the spectral ADMs, in practice we used ERA-40 reanalyses from four months (January 2002, April 2002, July 2002, and October 2001) to build clear-sky and cloudy-sky ADMs over ocean, and the same four calendar months in 2005 from the ERA-Interim to build clear-sky ADMs over land and desert, and clear-sky and cloudy-sky ADMs over snow. For each surface type, at least several hundreds of profiles over the globe are randomly chosen to construct the spectral ADMs.

For clear-sky scene types over ocean, land and desert [Huang et al., 2008; Chen et al., 2013]: the inputs to MODTRAN5 are temperature and humidity profiles, surface skin temperature from the training data sets, and surface emissivity. Spectral emissivity of the 18 IGBP surface types are obtained from the ASTER Spectral Library version 2.0 [Wilber et al. 1999; Baldridge et al. 2009]. The library covers 2 to 16 µm with a spectral resolution of 4 cm⁻¹. Figure 3.1.1 shows the spectral emissivity of such 18 surface types. For each profile selected, the surface type is determined based on the 1-km resolution land coverage data set from the U.S. Geological Survey (USGS) [Loveland et al. 2000], which has the same 18 IGBP surface types. The outputs from the MODTRAN5 are spectral flux and spectral AIRS radiance at viewing zenith angles from 0° to 45° with an increment of 3°. Anisotropic factor for each profile is computed using Eq. (3.1.1). The anisotropic factor stored in the ADMs is the mean of all selected profiles for each discrete interval (i.e., scene type) and for each VZA. Figure 3.1.2 shows a sample of anisotropic factor for three zenith angles, 0°, 60°, and 52.96° (the diffusive angle corresponding to the diffusivity factor of 1.66), respectively. At most wavenumbers, $R_v(\theta)$ decreases with viewing zenith angle, a dependence often referred to as “limb darkening.” For all angles, the anisotropic factors in the atmospheric window regions (850–1000 cm⁻¹, 1100–1200 cm⁻¹) and the water vapor pure rotational band (<500 cm⁻¹) are closer to one than those in other bands. The limb darkening is stronger in the ozone band (990–1070 cm⁻¹), the Q-branch of methane band (~1306 cm⁻¹), and the water vapor ν2 band (1200–2000 cm⁻¹). In contrast, $R_v(\theta)$ increases with viewing zenith angle in the center of the CO₂ band (~667 cm⁻¹), corresponding to “lime brightening.” The contrast between the CO₂ band and other bands is primarily due to the fact that the effective emission levels for channels at the CO₂ band center are located in the stratosphere rather than in the troposphere. The larger the viewing zenith angle (θ), the higher the effective emission level. As temperature increases with the height in the stratosphere, this leads to a larger radiance intensity when θ becomes larger. Therefore, if we define the frequency dependent diffusive angle, $\theta_{\text{diff}}$, as $\pi L_\nu(\theta_{\text{diff}}) = F_\nu$, then, for any $\theta < \theta_{\text{diff}}$, $R_v(\theta)$ will be smaller than one; for any $\theta > \theta_{\text{diff}}$, $R_v(\theta)$ will be larger than one. In the troposphere, temperature decrease with the altitude, which means that the opposite dependence of $R_v(\theta)$ on θ will occur.
Figure 3.1.1 Spectral emissivity of 18 different surface types from the ASTER Spectral Library version 2.0. Note for better visualization, the ordinate scale is not always same. CERES SSF algorithm uses seven surface types based on these 18 surface types: (1)-(5) combined as forest, (8) and (9) as savannas, (6) and (10)-(14) combined as grassland, (7) and (18) as dark desert, (15) as snow, (16) as bright desert, and (17) as ocean. This is adopted from Figure 1 in Chen et al. [2013].
Figure 3.1.2 The spectrally dependent anisotropic factors based on the U.S. 1976 standard atmosphere profile, for 0°, 60° and 52.96° (corresponding to the diffusivity factor of 1.66). This is adopted from Figure 2 from Huang et al. [2008].

**For cloudy-sky over the ocean** [Huang et al., 2010]: besides the inputs mentioned in the previous paragraph, the inputs also include cloud top height and cloud emissivity. To retain maximum consistency with the CERES ADMs, following approach is adopted for carrying out the simulation. First, 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 (Ts). Second, for each possible jointed discrete interval of pw and Ts, 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, Ts, f, ΔT_sc) is covered. Fourth, for each cloudy profile generated at the previous step, cloud emissivity is further varied to produce different pseudoradiance as defined in Loeb et al. [2005]. In summary, discretizing pseudoradiance(ψ) adds one more dimension to the original four dimensions of CERES-SSF LW ADM (pw, Ts, f, ΔT_sc) and, by doing so, Rv(θ) can be estimated for each joint discrete intervals of (pw, Ts, f, ΔT_sc, ψ).

**For cloudy-sky over the land and desert** [Huang et al., 2014]: given the definitions of sub-scene types in the CERES cloudy-sky ADMs are more complicated than those of the CERES clear-sky ADMs. The number of sub-scene types used in Huang et al. [2010] for cloudy-sky ADMs is two orders of magnitude greater than the number used in Huang et al. [2008] for clear-sky ADMs. However, unlike the clear-sky case, where surface spectral emissivity always affects the outgoing longwave radiation (OLR), some cloudy-sky cases have zero sensitivity to the surface spectral emissivity. For example, if the cloud is overcast and optically thick, then no photon of any frequency originating from the surface can reach the TOA, which means that the spectral ADM built by Huang et al. [2010] for this cloudy scene type can simply be used over land without any modification. With this in mind, we developed a semi-empirical correction to the spectral ADMs developed by Huang et al. [2010]. The correction takes the land surface spectral emissivity into account and makes it useable for cloudy-sky measurements over land, thus bypassing the need to compute spectral ADMs using the more exact but time-consuming methods for all sub-scene types. Mathematical details can be found in Appendix A in Huang et al. [2014].

**For clear-sky and cloudy-sky over snow and sea ice surface** [Huang et al., 2014]: we explicitly build spectral ADMs for each sub-scene type of snow and ice surfaces defined in Table 3.1.3. In this case such an approach is computationally affordable because the atmosphere above snow and ice surfaces is usually dry and cold and the lower troposphere is often nearly isothermal. As a result, much fewer sub-scene types are needed compared to other land surface types [Loeb et al., 2005]. Total precipitable water and lapse rate are not used in the definition of clear-sky sub-scene types over the snow and ice surfaces while only 2 intervals are used for Ts and surface-cloud temperature difference (ΔT_sc). The clear-sky fraction (f_clr) is divided into six bins (0-0.001, 0.001-0.25, 0.2-0.5, 0.5-0.75, 0.75-0.99, 1.0). To better account for seasonal variation and improve performance, the spectral ADMs over the snow and ice surfaces are built separately for each season. This approach accommodates the seasonal cycle of surface temperature and other associated properties in the cryosphere better than a single set of spectral ADMs for all seasons.
3.2 Estimating Fluxes at AIRS Channels

This step is straightforward, and merely uses Eq (3.1.1). With the ADMs built in Section 3.1, we also need scene type information to derive spectral flux from AIRS spectra. Given there is no atmospheric retrievals available from AIRS footprints themselves, scene type information as well as clear-sky information are from the collocated CERES FOV as recorded in the CERES SSF product. A CERES FOV is deemed as clear sky if the coincident MODIS pixel-level cloud coverage within the CERES FOV is ≤0.1% [Geier et al., 2001; Loeb et al., 2003].

3.3 Estimating Fluxes over Frequencies Not Covered by AIRS

In order to obtain spectral fluxes over the entire thermal-IR spectral range, a scheme has to be developed to estimate spectral fluxes at frequencies without the AIRS coverage. AIRS has no coverage at frequencies lower than 649.6 cm\(^{-1}\) and between 1613.9 and 2000 cm\(^{-1}\). AIRS has 12 modules assembled on the focal plane [Aumann et al., 2003], each having its own spectral range. The spectral ranges of neighbor modules might overlap with each other. As a result, a few spectral ranges are sampled by more than one module. Meanwhile, the modules do not provide a continuous coverage from 649.6 cm\(^{-1}\) and 1613.9 cm\(^{-1}\). For example, no AIRS channel covers 1136.6–1217.0 cm\(^{-1}\) and 1046.2–1056.1 cm\(^{-1}\). To address the spectral coverage issue, the following strategy is adopted to cover the entire spectral range from 10 cm\(^{-1}\) to 2000 cm\(^{-1}\):

1. For the spectral range continuously covered by AIRS, AIRS channel frequency is used. For the spectral range sampled by two overlapped channels, only one channel is kept and used in subsequent analysis.
2. Frequency gaps between 649.6 cm\(^{-1}\) and 1613.9 cm\(^{-1}\) are covered with channels having the same spectral resolution as the nearest AIRS channels.
3. For 10 cm\(^{-1}\) to 649.6 cm\(^{-1}\), it is covered with channels at a spectral resolution of 0.5 cm\(^{-1}\), approximately the same resolution as the nearest AIRS channel.
4. For 1613.9 cm\(^{-1}\) to 2000 cm\(^{-1}\), it is covered with channels at a spectral resolution of 1.5 cm\(^{-1}\), approximately the same resolution as the nearest AIRS channel.

Hereafter, the above four sets of channels are referred to as channel sets 1–4, respectively.

For AIRS channels in set 1, radiance \(I_v\) can be converted to the spectral flux \(F_v\) using the spectrally dependent ADMs described in section 3.1. For channels in the sets of 2–4, a multi-regression scheme based on the Principal Component Analysis is used to obtain the corresponding spectra fluxes. Parameters in the regression scheme are derived based on the ECMWF profiles and synthetic spectra. For every ECMWF profile falling into a given discrete interval, the synthetic spectral fluxes at all channels set 1–4 are computed. Spectral EOF analysis (principal component analysis in the spectral domain) [Haskins et al., 1999; Huang et al., 2003; Huang and Yung, 2005] is then applied to the collection of synthetic spectral fluxes to derive a set of orthogonal basis in the frequency domain,

\[
F_v = \bar{F}_v + \sum_{j=1}^{N} e_j \phi^j_v
\]  

(3.3.1)

where \(F_v\) is the synthetic spectral flux at frequency \(v\) from one ECWMF profile and \(\bar{F}_v\) is the average of all synthetic spectral fluxes at \(v\). \(N\) is the total number of channels, \(\phi^j_v\) \((j = 1 - N)\) are
the principal components (unitary vectors) that consist of a complete set of orthogonal basis in the $N$-dimensional space, and $e_j$ is the projection of $(F - \bar{F})$ onto the $j$-th principal component $\phi_j$. In practice, it is found that 99.99% variance can be explained by the first 20 or even less principal components. Therefore, we only retain the first $M$ principal components that account for 99.99% variance. In the matrix form, it means

$$F - \bar{F} \approx [\phi^1, \phi^2, ..., \phi^M] \begin{bmatrix} e^1 \\ e^2 \\ \vdots \\ e^M \end{bmatrix} = \Phi e$$  \hspace{1cm} (3.3.2)

where $F, \bar{F}, \phi^1, \phi^2, ..., \phi^M$ are vectors with a dimension of $N$ ($N \gg M$). Correspondingly, $\Phi$ is an $N \times M$ matrix and $e$ is an $M \times 1$ vector. Note that the total number of channels in channel sets 1–4 is $N$. The total number of AIRS channels ($N_{\text{AIRS}}$) is smaller than $N$ but much larger than $M$. Since Eq.(3.3.2) holds for all channels, if we use AIRS in subscript to denote a set of valid AIRS channels, we still have

$$F_{\text{AIRS}} - \bar{F}_{\text{AIRS}} \approx \Phi_{\text{AIRS}}e$$  \hspace{1cm} (3.3.3)

Note that $F_{\text{AIRS}}$ could be derived from AIRS measurement as described in section 3.2. $\bar{F}_{\text{AIRS}}$, on the other hand, are the mean spectral fluxes at the AIRS channels as derived from the set of synthetic spectra mentioned before. Eq. (3.3.3) implies a least-square solution

$$e \approx (\Phi_{\text{AIRS}}^\ast \Phi_{\text{AIRS}})^{-1}\Phi_{\text{AIRS}}^\ast(F_{\text{AIRS}} - \bar{F}_{\text{AIRS}})$$  \hspace{1cm} (3.3.4)

where $\Phi^\ast$ is the transpose of $\Phi$; Once $e$ is obtained for every qualified AIRS observation, Eq. (3.3.2) can be used to derive the spectral flux at each channel in sets 1–4, the channel sets not covered by the AIRS instrument. In practice, because of $N_{\text{AIRS}} \gg M$, $\Phi_{\text{AIRS}}$ is well-conditioned for every discrete intervals and inversion of $(\Phi_{\text{AIRS}}^\ast \Phi_{\text{AIRS}})$ is numerically stable.

4.0 Validations

4.1 Theoretical Validation

For theoretical validation, synthetic AIRS spectra are used to derive the spectral fluxes and such spectral fluxes are compared with those directly computed from the MODTRAN5. ECWMF ERA-40 6-hourly temperature and humidity profiles in a different year and a different month from those ECWMF data used in section 3.1 are randomly selected, classified to appropriate discrete intervals, and then synthetic AIRS spectra at different zenith angles and LW spectral fluxes are computed from the MODTRAN5. The differences between the spectral fluxes (or the broadband OLR) predicted from the synthetic AIRS spectra and the ones directly computed from the MODTRAN5 are examined. This validation lets us assess the whole algorithm without concerning the accuracy in spectroscopy and forward modeling since the MODTRAN5 is used as a surrogate of radiative transfer in the real world.

Figure 4.1.1a shows such differences for three different viewing zenith angles: 0°, 21°, and 45°. For all three angles, the mean differences for any discrete interval are generally within ±0.5 Wm$^{-2}$. The standard deviations are no more than 1.5 Wm$^{-2}$. The maximum and minimum differences
from the individual comparisons are within ±5 Wm$^{-2}$. The differences have no noticeable
dependence on either the zenith angle or the discrete interval. The OLR differences for other
viewing zenith angles are consistent. Figure 4.1.1b shows the mean differences of spectral fluxes
for each ADM discrete interval and one viewing zenith angle (21°). For all spectral intervals, 93% of
them has a mean difference within ±0.02 Wm$^{-2}$ per 10 cm$^{-1}$ and 98.7% of them has a mean
difference within ±0.05 Wm$^{-2}$ per 10 cm$^{-1}$. The largest absolute differences are seen mostly in two
ADM discrete intervals (intervals 4 and 9), which are no more than ±0.06 Wm$^{-2}$ per 10 cm$^{-1}$ (in
fraction, no more than ±5%). The bias patterns for other viewing zenith angles are similar (not
shown here).

Figure 4.1.1 (a): Difference between the clear-sky OLR predicted from the synthetic nadir-view AIRS spectra (0°,
21°and 45° zenith angles) and directly computed clear-sky OLR from MODTRAN5 for 14 discrete intervals over
tropical ocean shown in (c). The diamond is the mean difference, the error bar shows the mean ± standard deviation,
the dashed lines are the maximum and minimum differences for all random profiles in a given discrete interval.
(b): The mean difference between the predicted TOA spectra fluxes based on synthetic AIRS spectra and the
directly computed TOA spectral fluxes from MODTRAN5 for each ADM discrete interval. The spectral flux is
computed for every 10 cm$^{-1}$ interval from 10 to 2000 cm$^{-1}$. These are adopted from Figures 5 and 6, and Table 1
in Huang et al. [2008].
Figure 4.1.2 Same as Figure 4.1.1, but for clear-sky scene types over the land and desert surfaces (Upper: daytime; lower: nighttime). This is adopted from Figures 3 in Chen et al. [2013].

Figure 4.1.2 shows the mean spectral flux difference for clear-sky scene types over the land and desert surfaces (upper: daytime; lower: nighttime). Generally the differences are within ±0.02 Wm⁻² per 10 cm⁻¹ with only a few exceptions: the largest differences (~0.03-0.06 Wm⁻² per 10 cm⁻¹) are seen between 200-600 cm⁻¹ for two discrete intervals that have a small lapse rate or even an inversion boundary layer and either a warm surface underneath a dry atmosphere or a cold surface underneath a humid atmosphere. Only a limited number of cases from our training data sets are found for such intervals. The largest negative difference found is ~ -0.03 Wm⁻² per 10 cm⁻¹ around the ozone band for the discrete interval with an inversion layer and a warm surface underneath a dry atmosphere. Similar to the case for clear-sky over the ocean in Huang et al. [2008], the difference is not sensitive to the choice of daytime and nighttime profiles, nor is it to the viewing zenith angles.
We examined the mean broadband OLR and spectral flux difference for 32 randomly selected discrete intervals for cloudy-sky cases: cloud with inversion boundary layer, low clouds, middle clouds, and high clouds. Figure 4.1.3a show the mean broadband OLR and spectral flux difference for eight discrete intervals that have the largest discrepancies between computed and estimated OLR. The mean difference is between −3.66 and 1.11 W m\(^{-2}\). The standard deviation is within 2.94 W m\(^{-2}\) and maximum difference for any individual case is within ±12.9 W m\(^{-2}\). For all three zenith angles examined here, the largest differences are always seen in the H2 interval, which 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 data set 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. For the rest 24 discrete intervals that we examined, the OLR difference is within ±5 W m\(^{-2}\) and the spectral flux difference is also generally smaller than the 8 discrete intervals. The largest absolute spectral difference (~±0.025 Wm\(^{-2}\) per 10 cm\(^{-1}\); Figure 4.1.3c) 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%). The largest relative difference (Figure 4.1.3d) is only about
± 3.6%, which is mostly seen in the water vapor v2 band (>1300 cm⁻¹), a band contributing only
2–3% to the broadband OLR.

The good agreement between the “predicted” and the “directly computed” spectral fluxes indicates
that when the uncertainties in spectroscopy parameters and radiative transfer modeling are
excluded, the algorithm is capable of obtaining spectral fluxes at 10 cm⁻¹ intervals with enough
confidence.

4.2 Comparison with Collocated CERES Observations

This validation uses the algorithm to derive the broadband OLR from the AIRS spectrum and
compares it with the collocated CERES OLR. This validation is more rigorous in the sense that all
realistic uncertainties, such as those in spectroscopy, forward modeling, and collocation strategies,
are taken into account. In our study OLR_AIRS is compared to the collocated OLR from the CERES
SSF product (hereafter, OLR_CERES). Uncertainty of inverted CERES OLR is about 1% [Loeb et al.,
2007]. Given that the typical OLR values vary between 200-300 Wm⁻², the absolute bias of CERES
OLR is about 2–3 Wm⁻².

Note that in figures below in this section, OLR_CERES is based on CERES Edition 4A
(OLR_CERES in previous published papers are based on CERES Edition 3A). The results using
CERES Edition 4A are comparable to previous studies using CERES Edition 3A. The
OLR_AIRS is not the OLR product contained in the AIRS Level-2 and Level-3 data sets. (The
OLR product in the AIRS Level-2 and Level-3 data sets is computed as a function of AIRS
retrieved products using a Rapid Transmittance Algorithm for computing OLR [Mehta and
Susskind, 1999]). Instead, OLR_AIRS here is the summation of AIRS Huang Spectral OLR
products over the frequencies, which makes it comparable to the CERES broadband OLR.

Figures 4.2.1 shows the histograms of OLR_AIRS-OLR_CERES differences based on all clear-sky
collocated observations in 2006. The histograms show Gaussian-like distribution. Over snow
surfaces, 99.6% and 99.9% of OLR_AIRS-OLR_CERES differences are within ±10 W m⁻² for daytime
and nighttime, respectively. Over non-snow surfaces, 99.1% and 99.99% of the differences are
within ±10 W m⁻² for daytime and nighttime, respectively. The mean difference is less than 2.2
Wm⁻² for footprints over snow surface and less than 1.2 Wm⁻² for footprints over non-snow surface.
The standard deviation is less than 2.5 Wm⁻² for either case. The counterpart based on all cloudy-
sky observations in 2006 is shown in Figures 4.2.2. The mean difference is less than 3.7 Wm⁻² for
footprints over snow surface and less than 1.9 Wm⁻² for footprints over non-snow surface. The
standard deviation is less than 4 Wm⁻² and 6 Wm⁻² for snow and non-snow surfaces, respectively.
Figure 4.2.1 The histogram of differences between OLR estimated from real AIRS spectra and the collocated CERES OLR (OLR_{AIRS}-OLR_{CERES,EVI}) for clear-sky footprints over the globe in 2006.

Figure 4.2.2. Same as Figure 4.2.1 but for cloudy-sky footprints over the globe in 2006.
Figure 4.2.3. Maps of annual-mean differences between clear-sky OLR estimated from AIRS radiances and the collocated CERES clear-sky OLR (OLR$_{AIRS}$ - OLR$_{CERES}$) for the year of 2006. (a) clear-sky daytime only and (b) clear-sky nighttime only. (c) and (d) are same as (a) and (b) but for cloudy-sky. Individual results are averaged onto 2.5°×2° grids for the plotting.

Figure 4.2.3 shows the geographical maps of annual-mean OLR$_{AIRS}$-OLR$_{CERES}$ differences in 2006, gridded onto 2.5°-by-2° (longitude by latitude). Four panels are for clear-sky daytime and nighttime (upper row) and for cloudy-sky daytime and nighttime (lower row), respectively. In general, the annual-mean clear-sky differences are within ±2 Wm$^{-2}$. For the clear-sky daytime, the largest differences (~±6 Wm$^{-2}$) exist in Tibet Plateau and some areas in the tropical East Africa. The clear-sky nighttime differences are generally smaller than the daytime counterparts over the land, but slightly larger over sea ice regions. The differences over the extra-tropical oceans tend to be modestly positive (~2 Wm$^{-2}$) for both daytime and nighttime observations. The differences over cloudy-sky daytime and nighttime are more uniform than the clear-sky difference. The annual-mean cloudy-sky differences are ~2 Wm$^{-2}$, with the largest nighttime difference about 5 Wm$^{-2}$ over sea ice boundaries. Overall, the annual-mean OLR$_{AIRS}$-OLR$_{CERES}$ for clear-sky and cloudy-sky, daytime and nighttime are comparable with the uncertainty of OLR$_{CERES}$.

Figure 4.2.4 shows the monthly statistics of OLR$_{AIRS}$ – OLR$_{CERES}$ over all the snow and sea ice surfaces for each month in 2006. The monthly-mean clear-sky OLR differences vary from -1.55 Wm$^{-2}$ in the winter to 2.4 Wm$^{-2}$ in the summer for the daytime observations and from 1.74 Wm$^{-2}$ in the summer to 2.77 Wm$^{-2}$ in the spring for the nighttime observations. For cloudy-sky OLR, the daytime mean difference is 0.39–3.38 Wm$^{-2}$ and that for nighttime is 2.96–4.88 Wm$^{-2}$. The mean difference is large in the summer than in winter for both daytime and nighttime. The standard deviation of OLR$_{AIRS}$ – OLR$_{CERES}$ is 1–3 Wm$^{-2}$ for clear-sky and 2.9–3.9 Wm$^{-2}$ for cloudy-sky.
results. This seasonally dependent OLR difference is largely due to the time dependent snow coverage.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure4.2.4.png}
\caption{(a) Blue solid line denotes the monthly-mean OLRAIRS - OLR\textsubscript{CERES-Ed4} difference for all collocated clear-sky daytime observations over snow and ice surfaces in 2006. Red and green dotted lines denote the $\pm 1\sigma$ deviation from the mean, respectively. (b) Same as (a) except for clear-sky nighttime observations. (c) Same as (a) except for cloudy-sky daytime observations. (d) Same as (a) except for cloudy-sky nighttime observations. This is similar to Figure 1 in Huang et al. [2014], which used OLR from CERES-Ed3.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure4.2.5.png}
\caption{Figure 4.2.5 shows the annual statistics of OLRAIRS - OLR\textsubscript{CERES} for the period of 2003 - 2018. The clear-sky annual-mean difference is between 0.39 and 1.07 Wm$^{-2}$ for the daytime and between 0.57 and 0.89 Wm$^{-2}$ for the daytime. The range of cloudy-sky annual-mean difference is 1.48–2.10 W m$^{-2}$ for the nighttime and 1.69–1.87 W m$^{-2}$ for the daytime. These statistics are consistent with the statistics published before for all-sky observations over the tropical oceans and for clear-sky observations over lands [Huang et al. 2008, 2010; Chen et al. 2013]. Though the mean difference of OLRAIRS − OLR\textsubscript{CERES} is systematically positive for cloudy-sky cases, the fractional difference is only $\sim$0.9%. For the 16 years examined here, the standard errors of annual-mean differences are 0.20 W m$^{-2}$ and 0.08 W m$^{-2}$ for clear-sky daytime and nighttime; 0.20 W m$^{-2}$ and 0.05 W m$^{-2}$ for cloudy-sky daytime and nighttime, respectively. The numbers of collocated observations, clear-sky and cloudy-sky, are largely consistent from year to year.}
Figure 4.2.5 (a) Annual means of clear-sky $\text{OLR}_{\text{AIRS}} - \text{OLR}_{\text{CERES-Ed4}}$ differences over the entire globe for 2003 to 2018. The ticked vertical lines denote the $\pm 1\sigma$ deviation from the mean. Daytime and nighttime results are plotted separately. (b) Same as (a) except for cloudy-sky observations. (c) Number of collocated AIRS and CERES clear-sky observations in each year from 2003 to 2018. Daytime and nighttime results are shown separately. (d) Same as (c) except for cloudy-sky observations. This is similar to Figure 2 in Huang et al. [2014], which used OLR from CERES-Ed3.

5.0 Applications

Spectral OLR produced here can be used in climate studies for several purposes. First, it can be used to evaluate climate models, especially their simulated TOA flux in each LW spectral band. Such evaluation can avoid the compensating biases seen in the broadband flux evaluation, providing additional clues for diagnosing the model biases. It can also be used to understand the simulated cloud radiative effect in a similar way, by examining the band-by-band contribution to the longwave broadband cloud radiative effect. New insightful diagnostics can also be derived from the spectral flux and spectral cloud radiative effect. Following sections will describe such applications in detail. In addition, the spectral OLR products can also be used in understanding the spectral details of cloud radiative feedback [Huang et al., 2019] and in climate trend studies [e.g., Peterson et al., 2019].

5.1 Model Evaluation: Greenhouse Parameter

To illustrate the application of the derived spectral fluxes in GCM evaluation, we compare them with counterparts from the GFDL AM2 model simulation over the same period as forced by
observed SST. Details are in Huang et al. [2008]. The output of AM2 simulation is further sampled to ensure consistent temporal and spatial sampling patterns with the observations. All comparisons are based on such a subsampled AM2 data set. For simplicity, all comparisons are done with data collected during the ascending node only. Similar conclusions can be reached when the descending data are examined. Occasionally, in order to contrast the differences between the AM2 model and observations, 6-hourly NCEP-DOE reanalysis data [Kanamitsu et al., 2002] for the year of 2004 is used to generate a “third-party” comparison. The 6-hourly NCEP-DOE reanalysis data is processed in the same way as the AM2 model output and corresponding synthetic spectral fluxes are computed from the MODTRAN5.

To make a better comparison across all spectral bands, we focus on the clear-sky spectral greenhouse parameters [Ackerman et al., 1992; Frey et al., 1996] and the clear-sky broadband greenhouse parameters [Raval and Ramanathan, 1989] rather than the absolute spectral fluxes. The spectral greenhouse parameter is defined as

\[
g_{\Delta \nu} = \frac{\int_{\Delta \nu} B_{\nu}(T_s) d\nu - F_{\Delta \nu}}{\int_{\Delta \nu} B_{\nu}(T_s) d\nu}
\]

where \(T_s\) is the surface temperature, \(\Delta \nu\) denotes the spectral range, \(B_{\nu}(T_s)\) is the blackbody radiation at frequency \(\nu\) and temperature \(T_s\), and \(F_{\Delta \nu}\) is the clear-sky TOA outgoing flux over the same spectral range \(\Delta \nu\). The spectral greenhouse parameter, \(g_{\Delta \nu}\), is a measure of radiant energy over \(\Delta \nu\) trapped in the atmosphere. \(g_{\Delta \nu} = 0\) when the atmosphere is transparent over \(\Delta \nu\), and \(g_{\Delta \nu} \rightarrow 1\) when atmosphere is opaque over \(\Delta \nu\) and emits to space at a temperature much colder than the surface temperature. When \(\Delta \nu\) spans over the whole LW region, \(g_{\Delta \nu}\) becomes the broadband greenhouse parameter (hereafter, \(g_{LW}\)), representing the fraction of total radiant energy leaving the surface but trapped in the atmosphere.

Figure 5.1.1a shows the 2004 annual-mean clear-sky broadband greenhouse parameter derived from the AM2 simulation. ITCZ and SPCZ are clearly associated with the maxima of clear-sky \(g_{LW}\) (\(\sim 0.43–0.45\)) because the two convergence zones tend to have higher humidity throughout the whole troposphere than other areas. Meanwhile, the large-scale subsidence drying tends to decrease the humidity in the middle and upper troposphere while the entrainment of marine stratus tends to dry the lower-tropospheric layer just above its top [Houze, 1993]. Thus the minima of clear-sky \(g_{LW}\) (\(\sim 0.30\)) can be seen off the west coasts of major continents where the marine stratus prevails and large-scale subsidence is prominent. The differences in the clear-sky \(g_{LW}\) between the AM2 and AIRS (Figure 5.1.1b) indicate that the AM2 overestimates \(g_{LW}\) over most of the tropical oceans and such overestimation, in general, is positively correlated with the \(g_{LW}\) itself. In the ITCZ and SPCZ, the overestimation could be as large as 0.035–0.04 (\(\sim 7.8–8.9\%\)). Underestimations of \(g_{LW}\) by the AM2 happen in the subtropical oceans west of major continents and the central and eastern Pacific (90–180°W) in the deep tropics, regions featured with large-scale subsidence. As we shall see later, such overestimations and underestimations in the broadband \(g_{LW}\) have in fact originated from different spectral ranges.

Figure 5.1.1c shows the simulated annual-mean clear-sky spectral greenhouse parameters (hereafter, \(g_{\Delta \nu}\)) over the combined band of \(0–560\) cm\(^{-1}\) and \(1400–2200\) cm\(^{-1}\) (hereafter, the combined water vapor band). Both \(0–560\) cm\(^{-1}\) and \(1400–2200\) cm\(^{-1}\) bands are sensitive to relative humidity over a broad vertical layer approximately from 600 hPa to 200 hPa. As a result, the \(g_{\Delta \nu}\)
is highly correlated with the water vapor amount in the middle and upper troposphere, with maxima over the ITCZ and SPCZ and minima over the large-scale subsidence regions. The corresponding AM2-AIRS difference shown in Figure 5.1.1d is positive over all of the tropical oceans. This suggests that the AM2 overestimates the relative humidity in the middle and upper troposphere for the entire tropical oceans. We note here that satellite only samples the clear-sky footprints while the model output, even subsampled according to the satellite tracks, could be cloudy profiles. Therefore, such sampling difference might partly explain the differences seen in Figure 5.1.1d, especially over the convective regions. Huang et al. [2006] examined the same model and showed that the majority of model bias cannot be explained by such sampling difference alone. The $g_{\Delta v}$ in the window region (Figure 5.1.1e) is much smaller than both the $g_{\text{LW}}$ and the $g_{\Delta v}$ of the combined water vapor band: the AM2-simulated $g_{\Delta v}$ is only $\sim 0.12$–$0.15$ in the ITCZ and SPCZ and $\sim 0.04$ in the other tropical oceans. This is because, besides the water vapor continuum absorption, the atmosphere is almost transparent in the window region. The water vapor continuum absorption in this spectral region is proportional to the square of water vapor concentration, which makes it most sensitive to the water vapor concentration from the surface to $\sim 3$ km. The AM2-AIRS difference over this spectral range (Figure 5.1.1f) indicates an overestimation of $\sim 0.02$–$0.04$ in the large-scale convergence zones. In the large-scale subsidence regions, especially the oceans west of major continents, $g_{\Delta v}$ is underestimated by $\sim 0.01$–$0.02$. Same geographical patterns of the AM2-AIRS differences can be seen in other window regions as well (800–900 cm$^{-1}$, 1070–1200 cm$^{-1}$, not shown here). Such differences suggest an overestimation of the lower tropospheric (0–3 km) humidity in the large-scale convergence zones and an underestimation of it in the large-scale subsidence regions by the AM2. In the large-scale subsidence regions, the underestimation over the window regions (e.g., Figure 5.1.1f) slightly outplays the overestimation over the combined water vapor bands (Figure 5.1.1d) and other spectral ranges. As a result, the AM2 broadband $g_{\text{LW}}$ at these regions are slightly underestimated (Figure 5.1.1b). For the large-scale convergence zones, overestimations exist in both the water vapor bands and the window regions, which leads to a $\sim 10\%$ overestimation in the AM2 broadband $g_{\text{LW}}$.

Figure 5.1.1g shows the simulated $g_{\Delta v}$ for the spectral range of 990–1070 cm$^{-1}$ (the ozone band). Unlike other spectral ranges discussed above, the simulated $g_{\Delta v}$ of this spectral range has maxima in the subtropics rather than in the deep tropics because of the higher lower stratospheric ozone concentrations in the subtropics in comparison to the deep tropics. The AM2-AIRS differences (Figure 5.1.1h) show a zonally uniform pattern with minima in the deep tropics. Given the AM2 simulation is done with the 1990s ozone climatology, the AM2-AIRS differences here reflect (1) the difference of ozone distribution between the 1990s climatology used in the simulation and the actual ozone distribution in 2004 and (2) the lower stratospheric temperature difference between the AM2 simulation and the reality.
5.2 Model Evaluation: Cloud Radiative Effect

The band-by-band flux for cloudy sky observations together with band-by-band clear-sky flux, can be used to estimate band-by-band CREs in the same manner as the broadband CRE derived from ERBE or CERES observations. Then they can be compared to counterparts from GCM simulations. We also use the GFDL AM2 model as a case study here. Details are in Huang et al. [2010].

Figure 5.2.1 shows the spatial distributions of observed and simulated longwave cloud radiative forcing. The spatial distributions of broadband CRE (Figure 5.2.1 top) are largely consistent with each other. The largest contribution to broadband longwave CRE comes from the water vapor bands, consisting of \(~19.25\%\) of the total longwave CRE. As far as the spatial distribution for the water-vapor-band contributions to the longwave CRE is concerned (Figure 5.2.1 middle), observation and simulation agrees on vast area of the tropics, with the AIRS and CERES observations being slightly higher than the AM2 model. The largest discrepancies between AIRS and 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 and CERES (\(~5\%\) or less). Therefore, for the water vapor bands, the seemingly agreement on the tropical-averaged fractional contribution between observation and simulation (19.5% and 19.0% over 0–560 cm\(^{-1}\) > 1400 cm\(^{-1}\), respectively) is indeed due to compensating effect from different geographical regions. The contribution from 800 to 900 cm\(^{-1}\), a window band, to the longwave broadband CRE is only slightly smaller (\(~18.75\%\)) 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 (Figure 5.2.1, bottom) 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 CRE comparison alone.

![Figure 5.2.1](image)

Figure 5.2.1 (top) The annual mean longwave broadband CRE (left) from the AIRS and CERES collocated observations and (right) from the AM2 simulation. (middle) The fractional contribution of water vapor rotational band and vibrational v2 band to the annual mean longwave CRE. (bottom) Same as (middle) but for 1070–1200 cm$^{-1}$, a window band. This is adopted from Figure 6 in Huang et al. [2010].

5.3 Model Evaluation: IR-effective Cloud Properties

In order to provide useful diagnostics for model evaluation and to link the evaluations of the LW radiation budget with that of cloud macroscopic properties, in this section we further explore the concepts of IR-effective CTH and CA that were briefly discussed in section 4 of Huang et al. [2010]. Details are in Huang et al. [2014].

For a set of given spectral CRE (or band-by-band CRE as calculated by the GCMs), it is trivial to compute the $f_{\text{CRE}}(\Delta v)$, the fractional contribution of a band to LW CRE, and we denote this as $f_{\text{CRE data}}(\Delta v)$, where $\Delta v$ is the spectral interval or bandwidth. Then with appropriate temperature and humidity profiles, we can assume a 1-layer optically thick cloud at different altitude $z$ and compute corresponding $f_{\text{CRE}}$ denoted as $f_{\text{CRE,ICLD}}(\Delta v; z)$. We then define a cost function

$$
err(z) = \sum_{i=1}^{N} \left[ f_{\text{CRE,ICLD}}(\Delta v_i) - f_{\text{CRE data}}(\Delta v_i, z) \right]^2
$$

(5.3.1)
where the subscript \( i \) denotes the i-th spectral interval or band. The IR effective cloud top height (CTH_{eff}) is defined as the altitude for which \( err(z) \) attains its minimum, which can be obtained by either brutal-force calculation or bisection method by varying \( z \) in an off-line radiative transfer model such as MODTRAN5. With the CTH_{eff} and the same temperature and humidity profiles used in (5.3.1), we can compute the LW broadband CRE for an overcast sky with cloud top at CTH_{eff}, denoted as CRE_{overcast\_1CLD}(LW; CTH_{eff}). Then the effective cloud amount (CA_{eff}) can be defined as

\[
CA_{eff} = \frac{CRE(LW)}{CRE_{overcast\_1CLD}(LW; CTH_{eff})}
\]

where CRE(LW) is either the observed or GCM-simulated LW broadband CRE.

Simply put, CTH_{eff} and CA_{eff} are step-wise best fit of a one-layer opaque cloud model to the actual spectral (or band-by-band) CRE data, which might be obtained from observations, from GCM simulations, or from reanalysis. CTH_{eff} and CA_{eff} are derived from LW spectral CRE alone. Thus, strictly speaking they are radiative quantities and their diagnostics can be directly linked to broadband CRE and the radiation budget. At the same time, if they can be related to cloud physical macroscopic properties as well, they will enable connections between diagnostics of radiation budget and cloud simulations. Moreover, if CTH_{eff} and CA_{eff} diagnosed from monthly mean output are meaningful, such diagnostics can be then potentially applied to a wide range of model output such as those archived by the CMIP3 and CMIP5 (Coupled model intercomparison project, Phase 3 and Phase 5).

In practice, we find that, for given temperature and humidity profiles, the fitted CTH_{eff} changes little when spectral bandwidth varies from 10 cm\(^{-1}\) to the typical bandwidths of GCM radiation schemes. We also find that estimations of CTH_{eff} and CA_{eff} from monthly-mean data are more sensitive to the humidity than the temperature profiles when the water-vapor far-IR band is included in the fitting. This is because: (1) the contribution of upper tropospheric humidity to the far-IR band flux is significant as long as the cloud top is below the upper troposphere; and (2) upper tropospheric humidity can exhibit large variation within a month, especially in regions where wet and dry regimes alternate. Since we are aiming at having diagnostics of CTH_{eff} and CA_{eff} solely from monthly averaged band-by-band CREs, we excluded the far-IR band (or the combined band in the GCM which includes the far-IR band; Huang et al., 2013) in our fitting. For similar reasons, we exclude the ozone band in our derivation because the ozone vertical profiles can affect the fitting results and not all GCMs analyzed have employed realistically time-varying ozone profiles in the simulation. For results described in the following subsections, CTH_{eff} and CA_{eff} are derived from fitting the band-by-band CREs of all other LW bands. As shown in Figure 7b in Huang et al. [2010], for each band the change of \( f_{CRE} \) with respect to cloud top height is monotonic. Therefore, exclusion of two bands does not significantly affect the results of CTH_{eff} fitting.

We compare the CTH_{eff} and CA_{eff} from the collocated AIRS and CERES observations in 2004 with those from three atmospheric GCM simulations forced by observed SST for that year. The three GCMs used here are GFDL AM2, NASA GEOS-5, and CanAM4 by CCCma. Relevant details about these GCMs and the methodology for evaluating their band-by-band CREs can be found in Huang et al. [2013] and, for brevity, are not repeated here. In this subsection we only use
these simulations to provide preliminary evidence of the merit of $C T H_{\text{eff}}$ and $C A_{\text{eff}}$, instead of a full-scope data-model evaluation. Thus, this section will focus on zonal-mean quantities only.

Figure 5.3.1 shows the comparisons of zonal-mean $C T H_{\text{eff}}$ and $C A_{\text{eff}}$ among these data sets. Global-mean results are listed in Table 5.3.1. The overall features of both observations and three GCMs are similar to each other, such as the gradual decrease of $C T H_{\text{eff}}$ from the tropics to the poles, the maxima of IR-effective cloud amounts in the ITCZ zone and in the storm-track regions of both hemispheres. However, there are also noticeable differences. $C A_{\text{eff}}$ as inverted from the GEOS-5 band-by-band CREs is systematically lower by $\sim10\%$ globally than those from the collocated AIRS & CERES observations and the other two simulations. This underestimation is very likely related to the underestimation of cloud amount by the GEOS-5 model noted previously by other studies [Molod et al., 2012; Sud et al., 2013]. In terms of $C T H_{\text{eff}}$, however, the GEOS-5 simulation agrees with observations better than the other two GCMs.

**Table 5.3.1** The global-mean LW CRE, $C T H_{\text{eff}}$ and $C A_{\text{eff}}$ derived from the collocated AIRS and CERES observations in 2004 and from simulations forced by observed SST in 2004 by the GFDL AM2, NASA GEOS-5, and Canadian CCCma CanAM4 GCMs. This is adopted from Table 2 in Huang et al. [2014].

<table>
<thead>
<tr>
<th>Global-mean quantities</th>
<th>AIRS &amp; CERES</th>
<th>GFDL AM2</th>
<th>NASA GEOS-5</th>
<th>CCCma CanAM4</th>
</tr>
</thead>
</table>

Figure 5.3.1 (a) Zonal-mean IR-effective CTH derived from observed and simulated annual zonal-mean CRE in 2004. All data are shown in 4° latitude interval. (b) Same as (a) but for the IR-effective cloud amount. Black curves are from the inversion of band-by-band CRE from the collocated AIRS and CERES observations. Red, blue, and purple curves are derived from the simulated band-by-band CRE of the GFDL AM2, NASA GEOS-5, and Canadian CCCma CanAM4 GCMs, respectively. This is adopted from Figure 9 in Huang et al. [2014].
The CanAM4 simulation has higher $C_{TH_{eff}}$ than the observations in both polar regions than the observations. This is consistent with the findings in von Salzen et al. [2013], which compared CanAM4 simulations with CALIPSO observations and found that the simulated cloud tops in both Polar regions are higher than observed. Fig. 5.3.1 and Table 5.3.1 clearly show that, although the LW CREs of both GEOS-5 and CanAM4 are considerably lower than those observed, the reasons are different: the discrepancy is largely due to an underestimated global-mean $CA_{eff}$ for the GEOS-5 model and an overestimated global-mean $C_{TH_{eff}}$ for the CanAM4 model.

Although the global-mean LW CRE from the GFDL AM2 simulation agrees better with the observed value than that from the other two GCMs, this is achieved by a compensation between $C_{TH_{eff}}$ and $CA_{eff}$: the GFDL AM2 simulation yields lower $C_{TH_{eff}}$ than its observed counterpart for both the tropics and mid-latitudes, but also has $CA_{eff}$ higher than observed for the same regions. As a result, even its global mean $C_{TH_{eff}}$ is noticeably lower than the observed one by $\sim$1 km, its LW CRE does not differ from observations as in the GEOS-5 and CanAM4 models. These results suggest that such discrepancies in $C_{TH}$ and $CA$ can be distinguished via the step-wise inversion of $C_{TH_{eff}}$ and $CA_{eff}$ from the $f_{CRE}$ and LW CRE, but not directly from the broadband CRE diagnostics.

6.0 References


