**Synergistic Application of MISR Stereo Cloud Heights and Terra-MODIS Thermal Infrared Radiances to Estimate Multi-layered Cloud Properties**

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**Key Findings:**

1. Low bias, high-precision MISR low cloud heights are employed in a physics-based correction to MODIS CO2-slicing in multi-layered scenes.
2. Cloud-top pressure bias drops from 65 hPa to 5 hPa, resulting in a quartering of cloud-height and emissivity bias for cirrus over low cloud.
3. 88% of cloud-top pressure retrieval errors are bound by theoretical estimates, resulting in a near-closure of CO2-slicing error budget.

***Abstract***

Our longest, stable multi-decadal record of cloud-top pressure (CTP) and cloud-top height (CTH) are derived independently from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Multi-Angle Imaging Spectroradiometer (MISR) on the Terra satellite. Because of their use of a single cloud-layer assumption in their standard retrieval algorithms, they provide only a single CTP/CTH solution in multi-layered situations (~30% of all clouds). In the predominant multi-layered regime of thin cirrus over low clouds, MODIS exhibits significant biases in cirrus CTP and emissivity retrievals, while MISR’s stereoscopic technique accurately retrieves lower cloud CTH. Utilizing these complementary capabilities of MODIS and MISR, we develop and validate a 2-layered retrieval algorithm for accurate determination of CTP of both upper and lower layers and cirrus emissivity under conditions of thin cirrus over low clouds. This is achieved by using the MISR low-cloud CTH retrieval as a lower boundary condition to a CO2-slicing retrieval applied to MODIS infrared radiances for accurate retrievals of cirrus CTP and emissivity.

We evaluate the new 2-layered cloud retrievals against collocated International Space Station Cloud-Aerosol Transport System (CATS) lidar observations for multi-layered scenes. Relative to CATS, the mean bias and standard deviation of the upper cloud from the 2-layered retrieval is 5±80 hPa in CTP, compared to 65±85 hPa in the standard MODIS product – a ~90% reduction in CTP bias. The frequency of below-cloud-base retrievals of top-layer heights drop from 42% in standard MODIS product to 12% in our implementation. Upper cloud-layer emissivity and CTH from this 2-layered retrieval have their biases against CATS reduced by ~75% compared to standard MODIS. We also develop an error model for the new retrieval accounting for systematic and random sources of error and found that 88% of all residuals of the 2-layered retrieval against CATS were within the modeled 95% confidence intervals, indicating reasonable error closure. We show that the reduction in error from the new retrievals lead to a reduction in modeled top-of-atmosphere and surface longwave radiative fluxes ranging between 5 to 45 Wm-2, depending on the relative position and optical properties of the layers. Given this large radiative impact, we highly recommend that our new pixel-level 2-layered MODIS+MISR fusion algorithm be applied over the entire MISR swath and over the 22-year Terra record for public distribution. This would provide a first-of-its-kind climatology of 2-layered cloud systems from the morning orbit of Terra.

***Plain Language Abstract***

Our longest record of cloud-top pressure (CTP) and cloud-top height (CTH) from passive sensors on stable-orbit satellites come from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Multi-Angle Imaging Spectroradiometer (MISR) on the Terra satellite. While nearly 30% of global cloud cover is multi-layered, the standard algorithms of these sensors use single-layered cloud assumption and hence, provide single CTP/CTH solutions for multi-layered scenes. In the predominant multi-layered scenario of a thin cirrus over low cloud, MISR’s stereo CTH algorithm often accurately retrieves low cloud height whereas MODIS CTP systematically overestimates CTP (underestimates CTH). In this study, we have developed and implemented a 2-layered MODIS+MISR fusion CTP/CTH retrieval by using MISR’s accurate low-cloud CTH as an input to a modified MODIS CTP algorithm. This new algorithm combines the complementary capabilities of MISR and MODIS to distinguish thin cirrus from underlying low clouds and is capable of providing both cirrus and low cloud heights and cirrus emissivity for such scenes.

We evaluated the new algorithm by comparing against collocated International Space Station Cloud-Aerosol Transport System (CATS) lidar observations. We found our new fusion algorithm improves the estimates of high cloud CTP by ~90% over standard MODIS products, which results in ~75% increase in accuracy in other quantities derived from CTP, such as CTH and cloud emissivity. We found significant improvements to our estimates of modeled atmospheric longwave radiation as a result of the implementation of this algorithm. Owing to its large radiative impact, we suggest that the currently pixel-level MISR+MODIS fusion algorithm be applied to all 22 years (2000-2022) of the Terra record to facilitate public dissemination of the first 2-layered cloud climatology from the morning orbit of Terra.

1. ***Introduction***

The vertical and horizontal distribution of clouds induces gradients in 3D radiative and latent heating rates (McFarlane et al., 2008; Cesana et al., 2019; Athreyas et al., 2020), affecting atmospheric circulation and precipitation patterns (Y. Li et al., 2015; Voigt et al., 2021). As such, clouds play an important role in the Earth’s climate – yet, even after decades of research, they remain the key source of uncertainty in predicting future climate change under any given climate change scenario (Boucher et al., 2013). The cloud component of the uncertainty in climate model predictions arises, in part, from approximate sub-grid parametrization of cloud processes in those models (McFarlane, 2011). The sub-grid scale parameterizations are applied to microphysical (hydrometeor size and content) and macrophysical cloud properties (amount-by-altitude and cloud overlap), which together govern the radiative and hydrological properties of clouds. Accurate satellite records of these micro- and macro-physical properties, and their diurnal to long-term variability, are essential to provide empirical constraints on sub-grid cloud parameterizations and climate predictions (e.g., Zhou et al., 2013; Terai et al., 2016; Mace & Berry, 2017).

Our longest record of cloud properties that are stable over multiple decades (features of a desirable climate record) and from a single satellite platform comes from NASA’s flagship Earth Observing System (EOS) mission, Terra. It maintained a stable equator-crossing time (ECT; 10:30 am ± 15 minutes) for >20 years (2000-2022), with remarkable radiometric stability in its instruments. This long-term stability in Terra’s ECT makes it a unique climate record, since diurnal variability has not been aliased into the patterns of long-term variability.

Two of the instruments on Terra – the Multiangle Imaging Spectroradiometer (MISR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) – employ independent cloud-top height (CTH) retrieval algorithms. MISR retrieves CTHs through visible-channel stereoscopy (Mueller et al. 2013; Moroney et al., 2002; Muller et al., 2002), whereas MODIS employs infrared (IR) techniques, namely the CO2-slicing and 11µm brightness temperature techniques (Baum et al., 2012; Menzel et al., 2008). Both MODIS and MISR CTH retrieval algorithms assume a single cloud layer in the scene. This assumption is often not met in nature as multi-layered clouds occur frequently, with CALIPSO/CloudSat showing that >30% of all clouds occur under various degrees of overlap (Sassen et al., 2008; Joiner et al., 2010; Yuan & Oreopoulos, 2013; Li et al., 2015; Oreopoulos et al., 2017; Hong & Di Girolamo, 2020). By far the most dominant multi-layered cloud regime is a 2-layered system with thin cirrus overlying water clouds, followed by thin cirrus overlying mixed-phase clouds (Wang & Dessler, 2006; Oreopoulos et al., 2017; Hong and Di Girolamo 2020). Numerous validation studies against ground and space-based active sensors have shown that the presence of optically thin cirrus overlying low clouds leads to the most significant disagreements in retrieved CTH between MISR and MODIS (Naud et al., 2007; Marchand et al., 2010; Mitra et al., 2021), suggestive of the presence of independent information of the upper and lower cloud layers in the two datasets.

The path to improving the Terra record relies on exploiting this distinctiveness of the MODIS and MISR CTH techniques to estimate the properties of multi-layered clouds more accurately, as previously suggested (Naud et al., 2007; Mitra et al., 2021). CTH errors in multi-layered cloud regimes have been most recently and comprehensively studied for the MISR and Terra MODIS records by Mitra et al. (2021) using the experimental lidar known as the Cloud-Aerosol Transport System (CATS) (McGill et al., 2015; Yorks et al., 2016) which was in operation aboard the International Space Station (ISS) from 2015-2017. Comparison of MODIS Collection 6.1 CTH with CATS showed that the CTHs of thin cirrus in these multi-layered regimes were underestimated by more than 1 km on average. 42% of the retrievals detected a CTH below the cloud base detected by the lidar in these conditions. Such biases are common in thermal CTH retrievals and are due to the radiative influence of the lower cloud layer reaching the sensor through the optically thin cirrus at infrared wavelengths. On the other hand, the stereoscopic technique employed by MISR tended to retrieve the height of the lower layer with a high degree of precision and accuracy (-280±300 m), almost independent of the presence of thin cirrus when its optical depth < ~0.4. However, MISR failed to detect the higher layer >80% of the time (typically when cirrus optical depth < 0.4). This is due to the greater contribution of the optically thicker, more textured low clouds to the overall image texture that is used in stereoscopic retrieval. The distinct error characteristics of MISR and MODIS CTH retrievals indicate that there is information about multi-layering of clouds that can be extracted through fusion of the two retrieval methodologies. Here, we present a retrieval algorithm that makes use of the strengths of MISR’s sensitivity to low clouds and MODIS CO2-slicing technique’s sensitivity to high clouds to retrieve the coincident heights of up to two cloud layers as proposed previously (Naud et al., 2007; Mitra et al., 2021).

The remainder of the paper is organized as follows. Section 2 describes the theoretical underpinnings of the CO2-slicing algorithm for the detection of CTH and emissivity of thin ice clouds, and how it has been updated here to account for the presence of an optically thick low cloud. Section 3 describes the datasets used and the method of implementation of a variant of the MODIS single-layered CO2-slicing, along with the implementation of our 2-layer CO2-slicing technique. Section 4 documents the validation of the 2-layer CO2-slicing against coincident CATS lidar observations, along with an error budget analysis for the same. Net cloud radiative effect depends strongly on cloud overlap, as vertical hydrometeor distribution controls the relative strengths of longwave and shortwave effects (Li et al., 2011; L’Ecuyer et al., 2019), especially in the tropics (Kang et al., 2020). Section 5 presents theoretical estimates of the radiative impacts of using the 2-layer method over the 1-layer assumption. Concluding remarks follow in Section 6.

1. ***Theoretical Foundation***

CO2-slicing (Smith & Platt, 1978; Wielicki & Coakley, 1981), as used in MODIS (Menzel et al., 2008), makes use of the difference of clear- and cloudy-sky radiances from closely separated channels in the 13-15 µm CO2 absorption band, where the emissivity for ice clouds (such as cirrus) remain invariant across wavelengths within the band. Clear-sky radiance is required to account for the radiance reaching MODIS that originated from below thin ice clouds. The spectral clear-sky IR radiance, (neglecting scattering) at wavelength λ, reaching a satellite sensor viewing at nadir over a black surface (for simplicity here) is given by:

where, denotes the surface pressure, denotes the Planck radiance at temperature *T* and wavelength , with temperature defined as a function of pressure, P. (λ, P) denotes the atmospheric transmittance between *P* and the satellite. For a completely opaque cloud covering the instantaneous field of view (IFOV) of the sensor, the effective emissivity, which is the product of cloud fraction () within the IFOV and the cloud layer emissivity (), is unity. In this case, provided the opaque cloud is geometrically infinitesimally thin, the nadir radiance observed by the satellite, , is devoid of all emissions from below the cloud-top pressure (), and is given by:

In reality, clouds are often transmissive (< 1). Then, the observed nadir top-of-atmosphere (TOA) radiance is:

where, is the cloud fraction, and isoften interchangeably referred to as the effective cloud amount or effective emissivity. As effective emissivity for ice clouds is nearly equal for any two wavelengths (say and ) in the 15µm CO2-absorption band, we set them equal to each other, which, from Eq. 3, leads to

Cloudy-sky radiances are calculated for a number of discrete values, and the value of for which the right-hand side (RHS) and the left-hand side (LHS) have the least absolute difference is taken as the retrieved . Using this value of , we can solve for the cloud effective emissivity from Eq. 3, for either band, by:

For a 2-layer cloud system, with lower altitude cloud at of effective amount and an upper altitude cloud at of effective amount , Eq. 3 misrepresents the observed TOA IR radiation at the satellite sensor as it does not consider the emission from the lower cloud layer when the upper-layer is thin (i.e., < 1). In reality, for such a 2-layered system, the background emission (equivalent to the clear-cloudy sky radiance difference in a single-layered case) comes not only from the surface but also from the lower-layer, and hence, ) in Eq. 3 is modified to be , and the TOA IR radiance is:

Since is usually less than *,* the cloudy-clear radiance differences on the LHS of Eq. 4 are typically reduced when a second layer is present. Hence, simply using the single-layer strategy of Eq. 4 results in a CTP solution that is numerically greater than the true . Clearly, to arrive at a more accurate value of CTP for the upper cloud layer, one must correctly account for the emission from the lower cloud by modifying Eq. 4. Comparing Eq. 3 and Eq. 6, and assuming the lower cloud is black [i.e., , we estimate this emission as the term:

With this additional contribution being accounted for, again assuming (but now strictly for the upper cloud marked by ‘*u*’), Eq. 4 for multi-layered cases is recast as:

Similarly, Eq. 5 is adjusted to account for , and is recast from Eq. 6, as:

1. ***Methodology***

Section 3.1 briefly describes the datasets used in this study to both implement and validate our CO2-slicing algorithm whereas Section 3.2 describes the method of implementation and validation of our CO2-slicing technique against collocated CATS lidar observations.

***3.1. Data***

The operational MODIS Cloud Top Property algorithm [detailed in the MODIS Algorithm Theoretical Basis Document or ATBD (Menzel et al. 2015)], which produces the 1 km-resolution Collection 6.1 MOD06 product, uses gridded model output from the National Center of Environmental Prediction Global Data Assimilation System (GDAS) (Derber et al., 1991) for temperature and moisture fields and Reynolds Sea Surface Temperatures (Reynolds et al., 2007) to set up the forward model atmosphere. In our implementation, we have instead used gridded ERA5 Reanalysis products (Hersbach et al., 2020) at 0.25º-resolution, at 4 times a day (i.e., 0, 6, 12 and 18 UTC), to do the same. ERA5 is chosen over other reanalyses because it has been demonstrated to compare better against observations than older reanalyses (Tegtmeier et al., 2020; Tetzner et al., 2019), as well as to use its publicly available modeling error estimates for error budget analysis (see Section 4.2). ERA5 temperatures, specific humidity, and geopotential heights from all 37 ERA5 pressure levels are linearly interpolated as a function of the logarithm of pressure to arrive at the atmospheric state for the 101 pressure levels employed by the MOD06 algorithm. Surface pressures, temperatures (2m temperature over land and sea-surface temperature over oceans) and 2m dewpoint temperatures (to calculate surface moisture) are also used from ERA5 reanalysis, 4 times daily, to define surface temperature and near-surface humidity.

Well-mixed and trace gases (except ozone) are taken from standard atmospheric profiles (Northern/Southern Midlatitude Summer/Winter, Tropical) (Anderson et al., 1986); as are temperatures, specific humidity, and geopotential heights in the uppermost reaches of the atmosphere (i.e., pressures < 1 hPa; ERA5 reanalyses are not available at these altitudes). Between April-September, we assume a Northern Midlatitude Summer; while, between October-March, we assume a Northern Midlatitude Winter. The opposite is true for the Southern Hemisphere. The tropical profile remains invariant for all times of the year and is applied between 30ºN-30ºS, whereas the midlatitude profiles are chosen for latitudes poleward of ±30º. From Collection 6 MOD06, ozone profiles are taken from gridded GDAS output; however, for simplicity, we obtained ozone profiles similar to legacy MOD06 products – climatological ozone mixing-ratio profiles were estimated by linear interpolation in latitude and month among model atmospheres (Tropical, Midlatitude Summer/Winter). Surface emissivity is taken from the same global surface emissivity database used in MOD06 (Seemann et al., 2008).

The observed infrared radiances used in Equations 4/5 and 8/9 are taken from the Collection 6.1 MODIS Level 2 geocalibrated radiance product (MOD021KM). Terra MODIS uses Bands 33, 35 and 36 (13.3, 13.9 and 14.2 µm, respectively) for CO2-slicing CTP estimation [Band 34 (13.6 µm), also a CO2 absorption channel, is unused due to high noise]. Hence, the band-pairs 36/35 and 35/33 are used for estimating CTP (Equations 4 and 8). Band 31 (11.2 µm) radiances are used to calculate effective cloud amounts (Equations 5 and 9).

The low-cloud pressure, , is taken from MISR Level 2 CTH (in pressure coordinates). We use the 1.1 km-resolution MISR “wind-corrected” cloud height, from the TC\_CLOUD Version F01\_0001 product. The low cloud CTH is transformed to pressure coordinates through a linear interpolation between multi-level ERA5 geopotential height and the logarithm of pressure. MISR CTH is reported on the 1984 World Geodetic System (WGS84) ellipsoid, and hence, 0.25º-resolution nearest neighbor geoid heights were added to MISR CTH to obtain low cloud heights above mean sea level, before calculating CTP from it.

We validate our CO2-slicing technique by comparing against standard MODIS Cloud product (MOD06), as well as by comparing against coincident observations from the CATS lidar. Thus, our validation is restricted to latitudes traversed by the ISS orbit (±52º in either hemisphere). The CATS data is taken from the CATS Version 2.01 Level 2 Product, that reports lidar observations such as 1064 nm cloud-masked lidar backscatter at an along-track resolution of 5 km and a vertical resolution of 60 m. We use the same dataset of CATS CTH, layer depth and layer-integrated backscatter used in Mitra et al. (2021) for this study. Note that the filtering of multi-layered scenes in our study must be based solely on MISR and MODIS retrievals. Based on the discussion in Section 2, our algorithm is best suited for scenes with a thin ice-phase cloud overlying a vertically well-separated low cloud layer (further discussed in Section 3.2). To ensure these conditions are met in practice, we apply our algorithm only on scenes where the MOD06 product had used CO2-slicing for cloud-top detection (since CO2-slicing is only applied on ice-phase clouds) and where MODIS-MISR CTH difference > 1 km [suggestive of well-separated cloud layers, based on results of Mitra et., al (2021)]. Upon imposing these conditions, it is found that all scenes in the remaining dataset are indeed multi-layered according to CATS. 95% are likely 2-layered (for 92% of such cases, the CATS signal attenuates in the second layer). The remaining 5% pixels show attenuation in a third cloud layer. The final dataset constitutes 2790 pixels from 501 independent scenes (i.e., unique MISR and MODIS granules and CATS orbits), hence ~6 samples per scene (Supplemental Figure 1). Out of these, 305 (~11%) pixels are no-retrievals. This is largely due to the presence of radiance artifacts, such as striping. In the current study, such bad pixels are discarded from the analyses, but in future implementations, they will be dealt with by established procedures of MODIS radiance de-striping (Bouali & Ladjal, 2011; Weinreb et al., 1989).

IR emissivity of a cloud layer is related to visible optical depth () over the layer, as

where, equals the thermal IR optical depth (). The constant is taken to be 2.56 for ice clouds (Minnis et al., 1990). Estimates of visible optical depth () of the topmost cloud layer from CATS comes from a linear regression between layer-averaged integrated backscatter and layer-integrated optical depth for high clouds (CTH > 7 km) [detailed in (Mitra et al., 2021)]. These estimates of high cloud are converted to infrared effective emissivity (, assuming = 1) using Eq. 10 for validation. MODIS 1 km-resolution CTP, CTH, effective emissivity () and visible optical depth () are also used in validation, taken from the MOD06 product.

***3.2. Implementation of the CO2-slicing Algorithm***

For our implementation of the CO2-slicing algorithm, we have modified the original MOD06 Fortran Cloud-Top Property code (obtained from the MODIS Adaptive Processing System or MODAPS website) and wrapped it in Python. Salient features of the operational code and the modifications for our implementation are hereby discussed.

The MOD06 algorithm simulates clear- and cloudy-sky radiances using Equations 1 and 2, on 101 vertical pressure levels between 0.05 to 1100 hPa, taking gaseous absorption, surface emissivity and satellite zenith angle into account. These radiances are calculated for the channels centered on 11.2, 13.3, 13.6, 13.9 and 14.2 µm, using a transmittance model named Pressure layer Fast Algorithm for Atmospheric Transmissions (PFAAST) (Hannon et al., 1996), and further corrected for increased path-length along off-nadir viewing zenith angles. The usage of these modeled radiances along with the observed radiances from MODIS, in Eq. 4, requires that the cloud emissivity for pairs in the CO2-slicing spectral bands be nearly equal, which is more satisfied by ice clouds than water or mixed-phase (Zhang & Menzel, 2002). To ensure that the CO2-slicing algorithm is only applied on ice-phase, the MOD06 cloud phase detection algorithm is run ahead of the cloud-top algorithm. The CO2-slicing technique is applied only on such scenes with ice phase detection (11.2 µm brightness temperature technique is applied elsewhere). Here, we account for cloud phase by selectively working only on those pixels where the Collection 6.1 MODIS CO2-slicing had been previously used, as those pixels had already been flagged as confidently ice. Global comparison of Aqua-MODIS cloud phase with CLOUDSAT-CALIPSO data had shown that the MODIS cloud phase algorithm mischaracterizes multi-layered clouds with an upper ice layer as liquid or mixed in <1% of all cases (Marchant et al., 2016). This ensures confidence that pixels flagged as confidently ice by the Terra MODIS cloud phase algorithm is nearly always ice topped and hence, suitable for the implementation of our algorithm.

***3.2.1. Implementation of a Single-layered CO2-slicing and its Bias***

To obtain solutions for CTP and emissivity, Eq. 4 is solved iteratively between the surface and the tropopause, to obtain the value of that best reduces the difference between LHS and RHS of Eq.4. The tropopause is chosen as the upper limit of CTP solution, because the temperature profile is nearly flat across the tropopause, leading to non-unique solutions. The tropopause is taken to be the level of the highest altitude inflection point in the reanalysis temperature profile for pressures > 100 hPa. If many points satisfy such a condition, the lowest altitude point is chosen to be the tropopause. The solution of from Eq. 4 is then used in Eq. 5 using 11.2 µm radiances to estimate effective cloud amounts ().

The standard MOD06 algorithm calculates all possible CTP solutions, before only reporting a “best” solution through a “top-down” method that checks for the possibility of a higher wavelength solution before a lower wavelength or brightness temperature solution (i.e., 36/35 solution over 35/33 solution, over an IR BT solution) (Menzel et al., 2008). For a solution to be viable, the clear-cloudy radiance difference must exceed noise levels for each particular channel in that spectral band pair (designated to be 1.25, 1.0, 1.0 and 0.75 W m-2 sr-1 for Bands 36-33, respectively), and the solution from that channel must lie within a specific portion of the troposphere where the atmosphere is emissive for that spectral channel (i.e., for 36/35 pair, CTP solutions must be < 450 hPa; for the 35/33 pair, CTP solutions must be < 650 hPa). We, however, also output CTP and emissivity solutions from both band pairs for further examination.

To verify the implementation of our algorithm, we compared our 1-layer CTP solutions against MOD06 CTP for 500 CATS single-layer high cloud (CTH > 7 km) pixels from 42 independent scenes in January-February 2016. We find a mean (± standard deviation) difference in CTP between our implementation and MOD06 to be -5±30 hPa. For these scenes, the mean CTP bias (relative to CATS) for MOD06 is 20±30 hPa, whereas it is 15±35 hPa for our implementation. This provides confidence in our implementation, while also underscoring the fact that moving from GDAS to ERA5 reanalysis presumably has little impact on the single-layer CO2-slicing retrieval.

To estimate the systematic errors accrued from cloud overlap in CO2-sliced CTP, we conduct an experiment where we apply the 1-layered CO2-slicing on 2-layered cloud systems. For these experiments, we employ the forward model described in Section 3.2 to calculate synthetic radiances for the 2-layered system, except we include a lower, black cloud layer as in Eq. 6. We then use Equations 4 and 5 to retrieve the CTP under the assumption of a single layer and examine the resulting errors. This experiment is idealized in that it neglects any errors in the forward model. We perform retrievals on the synthetic two-layered systems for a climatological tropical atmosphere for different values of and . We calculate the overestimations of CTP above for four effective cloud amounts between 0.05-0.75 and for each of the spectral band pairs that are used by Terra MODIS. Results are shown in Figure 1. A few salient points are instantly noticeable – the highest overestimation of high-cloud CTP (i.e., an underestimation of high-cloud CTH) occurs in the 35/33 band pair for a combination of very thin high cirrus over a low cloud (provided the low cloud is sufficiently decoupled from the surface). It is unsurprising that the 35/33 band pair is more susceptible to the presence of low clouds, because there is a large reduction in the amount of near-surface radiation that reaches the satellite sensor in going from 13.3 to 14.2 µm due to increasing absorption by CO2. For the same high-low cloud combination and same spectral band pair, it is also unsurprising that the thinnest of clouds ( = 0.05) has the highest errors in CTP determination. As the lower cloud approaches either the high cloud or the surface, the 2-layered system essentially becomes indistinguishable from a single-layered high cloud; hence, in both these extreme conditions, the bias is reduced. These results are similar to the estimates of CTP bias arising from the application of a 1-layered CO2-slicing for 2-layered cloud systems by the HIRS/2 sounder (Figures 3, 5 and 6 in Baum & Wielicki, 1994) and MODIS (Figure 10 of Menzel et al, 2015).

Based on these findings, our bias-correction approach (Equations 8 and 9) for two-layered cloud systems will have the largest correction for well-separated cloud layers, provided the lower cloud-top is both sufficiently colder than the surface and warmer than the upper-layer cloud.

*Chart, scatter chart

Description automatically generatedFigure 1. Variation of CTP from MODIS CO2-slicing (under single-layer assumption) for Bands 36/35 (left panels) and 35/33 (right panels) for a high cloud at pressure = 200 hPa (upper panels) and 350 hPa (bottom panels), given a standard tropical atmosphere profile of water vapor (g/kg) and temperature (K; inset in c). Climatological profiles of ozone and trace gases are also taken. The lower cloud is assumed opaque, and the surface (1014 hPa) is a dark ocean. For each high-low combination, the experiment is repeated for cloud emissivities of 0.05 (blue), 0.1 (green), 0.3 (orange) and 0.75 (red).*

***3.2.2. Implementation of the 2-layered CO2-slicing***

The modification to the CO2-slicing solution for a 2-layered system involves replacing Equations 4 and 5 with Equations 8 and 9 in the CO2-slicing workflow, which, in turn, requires the computation of the term , given by Eq. 7. This step requires the value of MISR CTP (Section 3.1). The closest of the 101 MODIS levels to MISR CTP is taken as in Eq. 7. Solutions for from band pairs 36/35 and 35/33 are recorded. A best solution is also chosen using the “top-down” method. If no legitimate solution is found (Section 3.2.1), it is a no-retrieval.

All 2485 valid CTP retrievals are converted to CTHs, using ERA5 geopotential heights. All such retrievals are also used to estimate effective cloud amounts (using Eq. 9). MOD06 effective cloud amounts are also used for comparison. Following Eq. 10, effective cloud amounts are converted to visible optical depths (), assuming Note, the estimates for and are estimates of the high cloud optical properties retrieved after the radiative contribution of the lower cloud has been removed. In contrast, the corresponding MOD06 retrievals are effective estimates of those quantities retrieved using the combined radiation from both upper and lower cloud layers.

This aforementioned modification to the CO2-slicing is rooted in physical theory and makes use of Terra’s unique design for fusion between instruments, which allows us to improve the MODIS upper-layer CTP/CTH and emissivity, provided the layer is optically thin for MISR to retrieve CTH of the lower cloud [this is also the regime where MODIS CO2-slicing CTH errors are maximum (Mitra et al., 2021)]. To distinguish the new high cloud properties from the operational MODIS data variables, we shall refer to the new estimates of cirrus CTP/CTH, and as the **MISR-MODIS Fusion Product for Cloud-Top Height (MM\_CTH)**.

1. ***Validation***

In this section, MM\_CTH and MOD06 estimates of high cloud macrophysics and optical properties will be validated against CATS estimates of those quantities and the errors in our 2-layered CO2-slicing will analyzed with the goal of closing the error budget.

***4.1. Comparison with the CATS lidar***

To validate our new algorithm, we compare the results of high cloud CTP/CTH, high cloud effective emissivity () and visible optical depths () from MM\_CTH against concurrent MOD06 and CATS observations. We divide the validation of MM\_CTH along two lines – validation of high cloud macrophysics (CTP, CTH) and high cloud optical properties (, ).

***4.1.1. Validation of High-Cloud Macrophysical Properties***

As in Mitra et al. (2021), we take CATS CTH/CTP to be an unbiased truth in our analysis. CATS CTH is converted to CATS CTP, using ERA5 geopotential and standard geoid heights, in the same manner as MISR CTH to CTP conversion. Figure 2 shows the distribution of CTP/CTH differences between CO2-slicing techniques (MOD06 and MM\_CTH) and the lidar on the left panels, and the distributions of high cloud CTP/CTH from the 3 techniques (MOD06, MM\_CTH and CATS) on the right panels. The mean bias (±standard deviation) in retrieved CTP and CTH improves from 65±85 hPa and -1.6±2.3 km, respectively, for MOD06 to 5±80 hPa and -0.4±2.4 km for MM\_CTH. This represents a ~90% reduction in CTP bias and a ~75% reduction in CTH bias.

The reduction in the CTP/CTH bias for high-cloud retrievals results in improved high cloud macrophysical distributions (right panels of Figure 2), with the MM\_CTH distributions of CTP/CTH closely mirroring those from CATS. Mitra et al. (2021) showed that for 42% of all scenes with a thin cirrus overlying a low cloud, MODIS CTH lies below the vertical extent of the cirrus (i.e., lower than CATS cloud-layer base). The application of the 2-layered MM\_CTH reduces the instances of such below-cloud-base height retrievals to merely 12%.

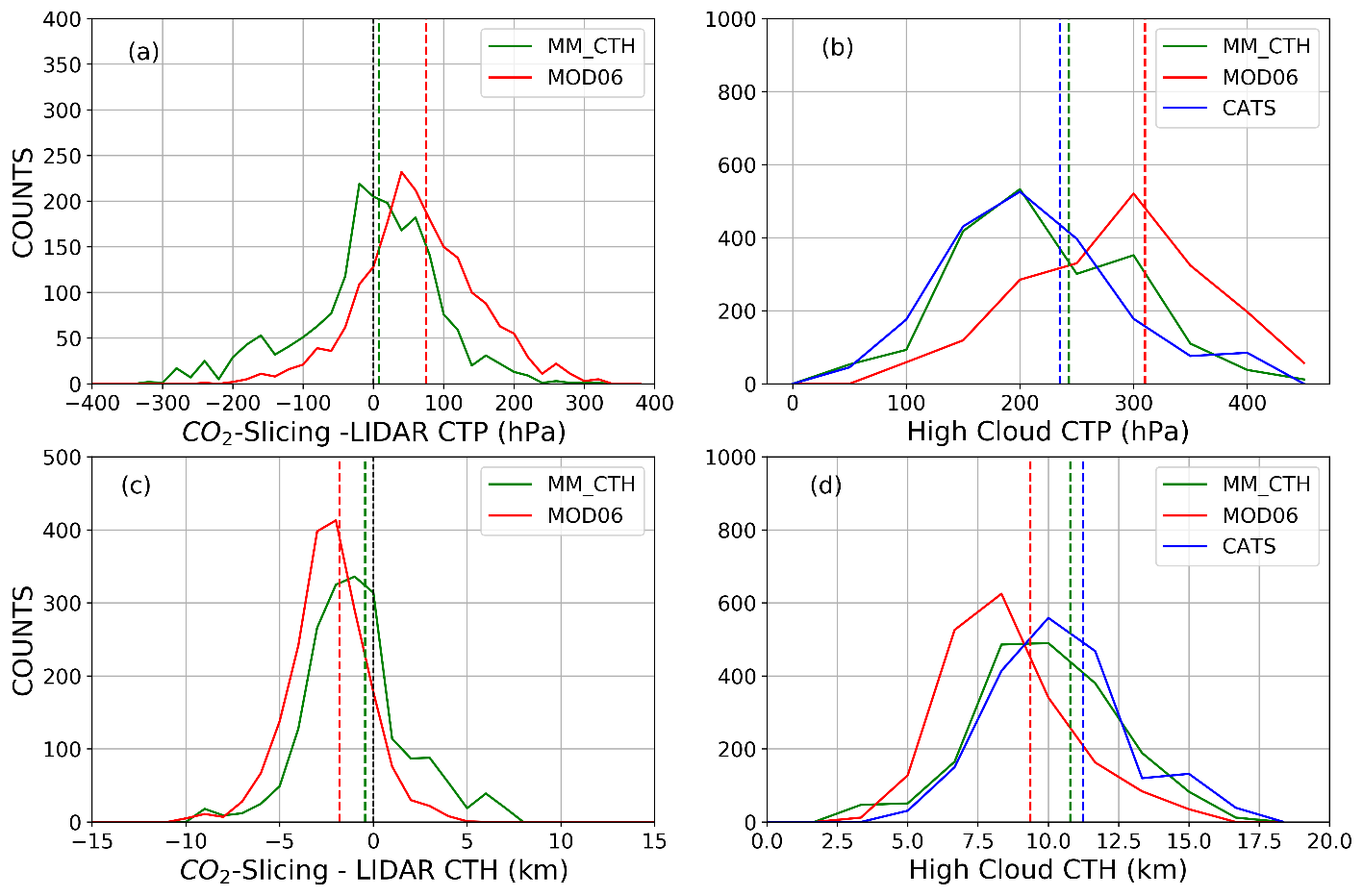
For the distributions of MM\_CTH minus CATS CTP and CTH (Figures 2a and 2c), we note the existence of a significant number of scenes (~4% of each distribution) where MM\_CTH appears to overestimate the value of CATS CTH by > 4 km (i.e., underestimate CTP > 100 hPa). Previous studies (Mitra et al., 2021; Rajapakshe et al., 2017) had identified these as scenes where the 1 km-resolution infrared sensor detects physically tenuous (e.g., broken cirrus) clouds, but the lidar’s 5 km-resolution algorithm picks the height of a lower, possibly horizontally continuous, cloud field. Here, we show that this assertion is indeed true by calculating the mean MISR-CATS CTH for scenes with MM\_CTH – CATS CTH difference > 4 km, and finding a mean difference of -0.5±0.5 km. This is close to MISR’s CTH accuracy for low clouds (Mitra et al., 2021). This suggests that, in these scenes, MODIS retrieved cirrus heights and CATS retrieved low cloud heights. Such an effect is noticeably smaller in the corresponding MOD06 distributions because MOD06 estimates of CTH (CTP) are lower (higher), and hence, closer to the CATS low-cloud retrievals.

Figure 2. Distribution of errors (left) in CTP (top panels; hPa) and CTH (bottom panels; km) from MOD06 (red) and MM\_CTH (green) and the distribution of high cloud macrophysics (right panels) for multi-layered scenes from MOD06 (red), MM\_CTH (green) and CATS (blue). The vertical dashed lines in each color represents the mean value of the quantities whose distributions are in that same color.

***4.1.2. Validation of High-Cloud Optical Properties***

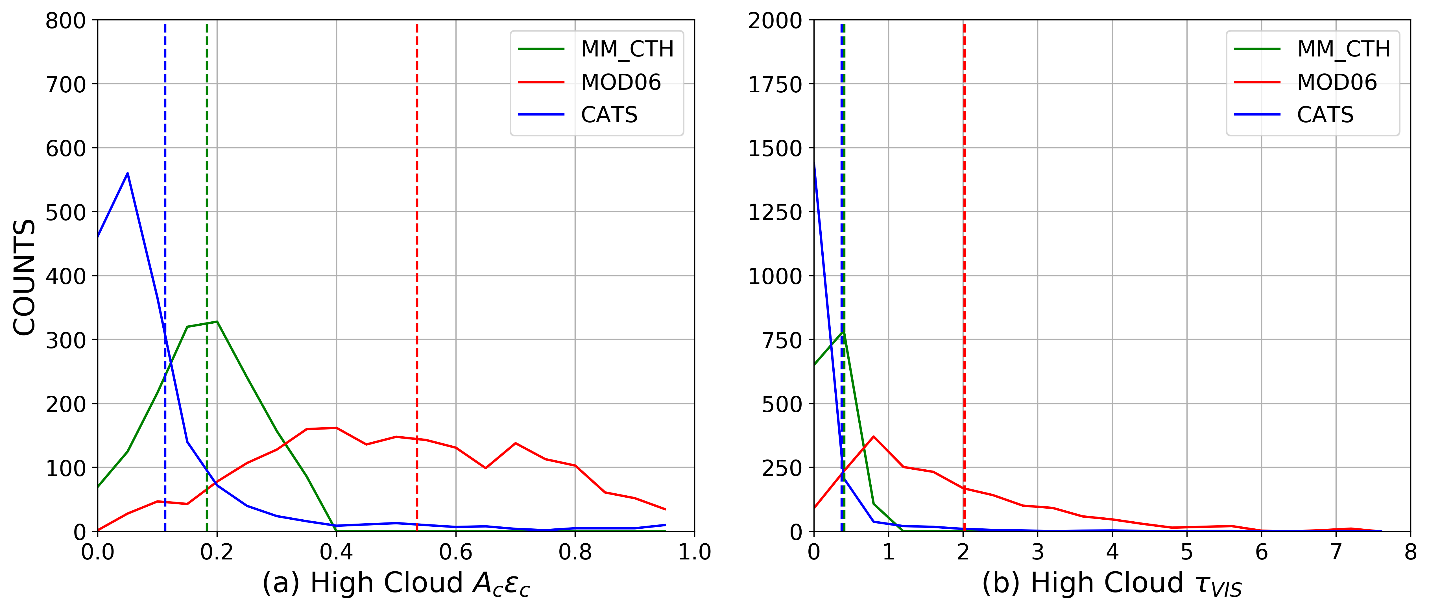
Unlike cloud-top properties (CTP and CTH), we do not have an unbiased estimate for cloud effective amount (. As a result, we have converted CATS to CATS by inverting Eq. 10 (assuming . Even though this is not an unbiased estimate of true , one can reasonably expect the CATS to be a closer estimate of true emissivity as compared to MOD06 , because MOD06 is an effective emissivity retrieved for all cloud layers in the atmospheric column. As shown in Figure 3, we have compared MM\_CTH estimates of and against CATS and MOD06 estimates of those quantities. The improvements in cloud macrophysical retrievals shown in Section 4.1.1 have propagated to improvements in retrievals of high cloud optical properties. From Fig. 3, we notice a ~75% increase in accuracy in both and for MM\_CTH over MOD06 (assuming ad hoc that CATS emissivity and are unbiased). These improvements lead to MM\_CTH distributions of high cloud emissivity and optical depths that are comparable to the corresponding distributions from the CATS lidar.

Figure 3. Distribution of effective emissivity (left) and visible optical depth (right) from MOD06 (red), MM\_CT (green) and CATS (blue) for high clouds in multi-layered scenes. The dashed lines in each color represents the mean value of the quantities whose distributions are in that same color.

The MOD06 estimates of and are both overestimations of true high-cloud optical properties because their individual retrieval methods do not remove the radiative contribution of the lower cloud. As a result, both are effective retrievals over all cloud layers. Improved estimates of upper-cloud optical properties (especially are crucial in the accurate representation and tuning of cloud radiative effects in models (which we demonstrate in Section 5). In Fig 4b, the MOD06 estimates of are from the standard MODIS bispectral optical depth retrievals (Platnick et al., 2017) which use visible channel radiances and separate pre-computed look-up tables for ice and water clouds. As such, since we are working on scenes where MODIS cloud phase detected ice, the ice look-up tables had been used to retrieve for a 2-layered multi-phase system. Here, we have improved the retrieval by improving our estimates of only the cirrus . However, with the improvements achieved by MM\_CTH in defining the CTP of the ice and water cloud layers, future work can design 2-layered ice + water/mixed phase cloud look-up tables to simultaneously retrieve the visible optical depths of both cloud layers present within the scene.

In the previous sections, we have presented the validation of MM\_CTH against CATS lidar. A detailed discussion of the CTP error budget follows in Section 4.2.

***4.2. The 2-layered CO2-slicing Error Budget Analysis***

In this section, we shall investigate the effect of various sources of systematic and random errors on MM\_CTH CTP (note that we do not repeat this exercise for effective emissivity as we do not have a truth dataset for that quantity). We consider the following sources of errors:

1. the uncertainty in MISR low-cloud stereo heights,
2. the covariance of modelling errors in ERA5 Reanalysis temperature and specific humidity,
3. the inherent noise in detected radiances from the MODIS spectral bands,
4. the effect of geometric depth or vertical extent of cirrus clouds,
5. the uncertainty in the geo-collocation of CATS, MISR and MODIS pixels,
6. the uncertainty incurred from the application of spatial interpolation to obtain atmospheric parameters at the 101 MOD06 vertical pressure levels,
7. the breakdown of the assumption that the low clouds are perfectly black, and
8. the effect of uncertainty in surface emissivity.

Empirical estimates are known (as explained below) for ERA5 co-variability, cirrus geometrical depth, MODIS radiance noise, MISR low-cloud CTH uncertainty, geo-collocation, and interpolation errors. However, we lack a ‘truth’ dataset for low cloud opacity and surface emissivity. Hence, error sources vii and viii will be dealt with in a different manner to the others.

We will run radiative transfer simulations over a range of 2-layered cloud combinations and use the simulated radiances in MM\_CTH retrievals to calculate CTP errors. We will then use the results from these simulations to construct error matrices that have the functional form: . Here, are the CTP, geometric depth, and the visible optical thickness of the high clouds in the simulations, whereas is the CTP of the low black cloud. refers to the band-pair being employed (i.e., either 35/33 or 36/35), and denotes the 5 climate zones introduced in Section 3.1. For each climate zone, we calculate CTP using the MM\_CTH technique for the following:

1. 10 values of (50 hPa intervals between 150 and 550 hPa), times
2. 6 values of (50 hPa intervals between 700 and 1000 hPa), times
3. 5 values of geometric depth (25 hPa intervals between 25 and 150 hPa), times
4. 8 values of (0.25 intervals between 0.25 and 2.5)

This leads to 2400 cases for each band-pair and for each climate zone. We choose the ranges for high cloud properties and from the distributions of high cloud properties and low cloud heights (in units of pressure) that we observed in the CATS and MISR data used in this study.

To model the expected variability in the first three error sources listed above (i.e., i, ii, and iii), we perturb these 3 quantities to derive 200 different realizations of each of the aforementioned 2400 cases. We do this to propagate the uncertainties in these quantities to uncertainties in simulated radiances and thereby, to uncertainties in retrieved CTP. This procedure is detailed below.

1. **Low-cloud CTP:** Mitra et al. (2021) noted that MISR low cloud CTH error is -230±300 m. This error is propagated to CTP error using the formula where, is the pressure uncertainty at a pressure level *P* corresponding to a height uncertainty of , for a pressure profile that varies with height according to the formula . Here, *P0*is the pressure at surface (z = 0), z is the altitude of the pressure level and H is the scale height of the atmosphere, given by the altitude where . For every instance of , we consider a biased estimate by taking the pressure-equivalent of MISR CTH – 230 m (using the form for *P(z)*, given above) and then create a distribution of low cloud-layer CTP by drawing 200 random samples from a normal distribution given by µ=0, σ =
2. **ERA5 Reanalysis Error:** To estimate the error-covariances of the ERA5 temperature and moisture profiles, we used the results of all model ensemble (Hersbach et al., 2020) that are publicly available along with ERA5 reanalysis (given by the ensemble mean). These ensemble members provide flow-dependent uncertainties based on propagation of assimilated measurement uncertainties as well as perturbations to physical tendencies. We took data from all grid cells over the globe over a day from each month of 2016 and calculated flow-dependent perturbations by subtracting each ensemble member from the ensemble mean. We then grouped the perturbations by latitude and season in the 5 pre-defined climate regimes (Section 3.1). Here, we estimated the error-correlations between all pressure levels of the profiles of temperature and moisture reanalysis, neglecting error-correlations between adjacent columns. Horizontal error correlations are neglected, as they are only relevant for the aggregation of pixel retrievals, not for individual pixel-level uncertainties. Upon comparing against empirical estimates of ERA5 uncertainty (Graham et al., 2019), we found that the ensemble uncertainty is similar to observed uncertainty for specific humidity. However, the ensemble uncertainty underestimates observed uncertainty of Graham et al. (2019) by a factor ranging between 4-6, depending on pressure level. To correct this discrepancy, temperature profile perturbations from the ERA5 ensemble data are inflated by a constant value of 5, for all pressure levels. For each climate regime, we then propagated the resulting errors to errors in CTP through Monte Carlo sampling. Specifically, we drew 200 perturbed profiles of temperature and specific humidity assuming multivariate Gaussian distributions. The mean value of these distributions are given by their climatological profiles and their covariance matrix is set as described above.
3. **Instrument Noise**: We introduced further perturbations to the calculated TOA radiances, by drawing 200 random samples from a normal distribution with µ=0, σ = 1 W m‑2. Here, we have set σ as the mean noise level for the Terra MODIS CO2-slicing channels (as noted in Section 3.2.1, the noise levels in Bands 33-36 varies between 0.75-1.25 Wm-2).

To model the error due to a finite cloud depth, we modify the gas-only model (Section 3.2) for clear-sky radiative transfer to include cloud. We simply prescribe a cloud optical depth, cloud-top and bottom pressure (based on our choices of listed in (a) to (d) above). We assume that cloud extinction is homogeneously distributed in pressure over the cloud depth. We verified our implementation using the analytic solution for an isothermal and non-scattering atmosphere. We use this model to simulate radiances in the CO2-slicing bands for geometrically thick, non-black clouds and estimate the CTP retrieval errors stemming from the infinitesimally thin high cloud assumption used in the CO2-slicing technique. Gas optics uncertainties are numerically insignificant (<<1% of instrument noise) (Hannon et al., 1996) and are hence, ignored.

With the major sources of systematic and random errors accounted for, we run the MM\_CTH algorithm for all 200 perturbed instances of each of the 2400 combinations of . We note the bias and standard deviation in CTP for each of those instances for comparison against observed error.

To account for further sources of random error (error sources v and vi), we estimated the uncertainty in CTP introduced by the process of geo-collocation of MODIS and CATS pixels. Mitra et al. (2021) showed a maximum uncertainty of 900 m in CTH due to the geo-collocation of MODIS and CATS pixels for CATS retrievals above an altitude of 5 km. Using the equation to propagate height errors to pressure errors given earlier, we estimate this collocation uncertainty (given by ) for all pixels. The errors in interpolating our CTP solutions to the discrete grid employed by the MODIS algorithm also result in an additional source of random error. This error, which we denote by is numerically equal to half the grid-spacing between the nearest two levels of a CTP solution. As in Mitra et al. (2021), the random error in CATS CTH (converted to a CTP error given by ) is equal to that associated with an equal probability of successful or failed retrieval over a 60 m CATS range gate, i.e., a random error of 30 m. Since, these sources of error are mutually independent, we estimate total random uncertainty (in a pixel-level retrieval) as where, is the error incurred from the various uncertainties in the radiative transfer simulations (sources i to iv), that are accounted by the standard deviation estimates from the error matrices, .

To then ascertain the fraction of pixels that are theoretically bound, we investigated the distribution of bias-corrected errors, normalized by , i.e., , where is the estimated value of CTP from the MM\_CTH method, is the observed (also, the assumed “true”) CTP from CATS, whereas, *bias* is the closest estimate of theoretical systematic error for a particular pixel from the error matrices, . We find 78% of all pixels to be within the bounds of 95% confidence interval (i.e., [-1.96, 1.96] in units of ). The remaining 17% (i.e., 95% minus 78%) of errors remain outside the purview of what can be constrained against empirically observed variables. We suspect that low cloud non-opacity and uncertainty in surface emissivity are the reasons behind these outliers.

We logically assert that surface emissivity is a less significant source of uncertainty than low clouds because in most multi-layered cases, the surface remains partly to nearly obscured by an opaque low cloud and >70% of all retrievals in our dataset are done by the 36/35 band pair (which is nearly insensitive to surface emissions; Menzel et al., 2015). Moreover, the effect of surface emissivity only becomes relevant in the very cases where the black low cloud assumption breaks down – e.g., for broken low clouds. Hence, we do not investigate surface emissivity separately. To investigate the effects of low-cloud properties, we first establish that non-opacity of low clouds (i.e., may arise due to the presence of sub-pixel low clouds (e.g., small trade wind cumuli) or due to the presence of optically thin low clouds with (i.e., ). To quantify the errors in such scenarios, we relaxed the condition of a low, black cloud by assuming low cloud effective amounts of 0.1 iterations between 0.1-0.9 for each of the 2400 cases. Effective IR emissivity of the low cloud is then converted to cloud optical depth (using Eq. 10), and the transmission profile is adjusted accordingly. Surface emissivity is taken to be 1. In spite of the non-black low cloud, we still solve for the high cloud CTP assuming . The mean and standard deviation of the resulting errors over all possible cases, for each value of low-cloud effective amount and MODIS CO2-slicing band pair, are computed and shown in Figure 4. For the Band 36/35 pair, unsurprisingly (since this pair is less sensitive to surface emission), low-cloud semitransparency leads to lower and nearly constant error, irrespective of the low cloud amount (especially, for . However, the standard deviations of error for the Band 35/33 pair drops significantly as low cloud amount increases.

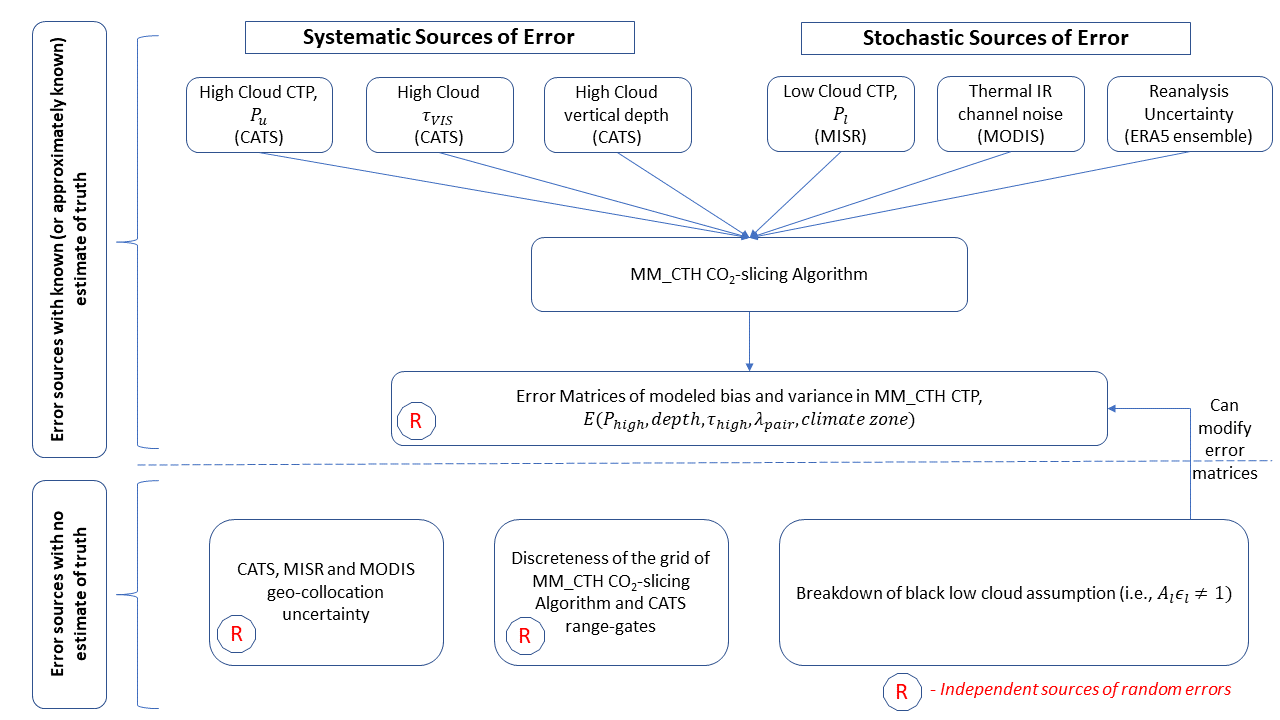
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Figure 4. Distribution of errors in CTP (in hPa) incurred from the breakdown of the assumption of a black low cloud, from MODIS Band Pair 36/35 (left) and 35/33 (right) for different values of thermal IR effective emissivity () of the low cloud.

Taking the effect of non-opaque low cloud into account, we redefine the bias-corrected errors to mean , where is defined as the mean bias for both band-pairs in Fig 4, weighted by their relative frequency of usage in our dataset. We calculate distributions of bias-corrected error (in units of σ) for all values of and study the percentage of errors which lie within 95% CI in each case. Taking low clouds into account results in > 80% errors lying within 95% CI for all values of . We find that the maximum agreement between theoretical and observed errors is achieved when 88% of all bias-corrected errors lie within 95% CI for =0.3. Here, we note here that the expected dominant effect of low-cloud heterogeneity probably arises from occurrence of sub-pixel clouds. Assuming , these would mean that the most likely value of low-cloud fraction in our dataset is . If cloud area is taken as , where is the cloud radius and MODIS pixels are of 1 km resolution, then a low-cloud fraction of 0.3 would suggest that the most probable diameter for low clouds in our dataset is 620 m. This makes conceptual sense as our dataset has samples from both fair-wind trade cumulus regions with typical cloud diameters of ~450 m (Zhao and Di Girolamo, 2007) and from regions with more stratiform clouds (that would typically cover the entire 1 km MODIS pixel). Thus for =0.3, only 7% of errors are not constrained by our theoretical estimates (denoted by 95% CI), we can say that a near-closure of the MM\_CTH CO2\_slicing error budget has been achieved.

The error budget analysis adopted in this section is summarized in Fig. 5.



1. ***Radiative Impact of a 2-layered CO2-slicing***

Figure 5. Schematic summarizing the error analysis methodology adopted for MM\_CTH CTP.

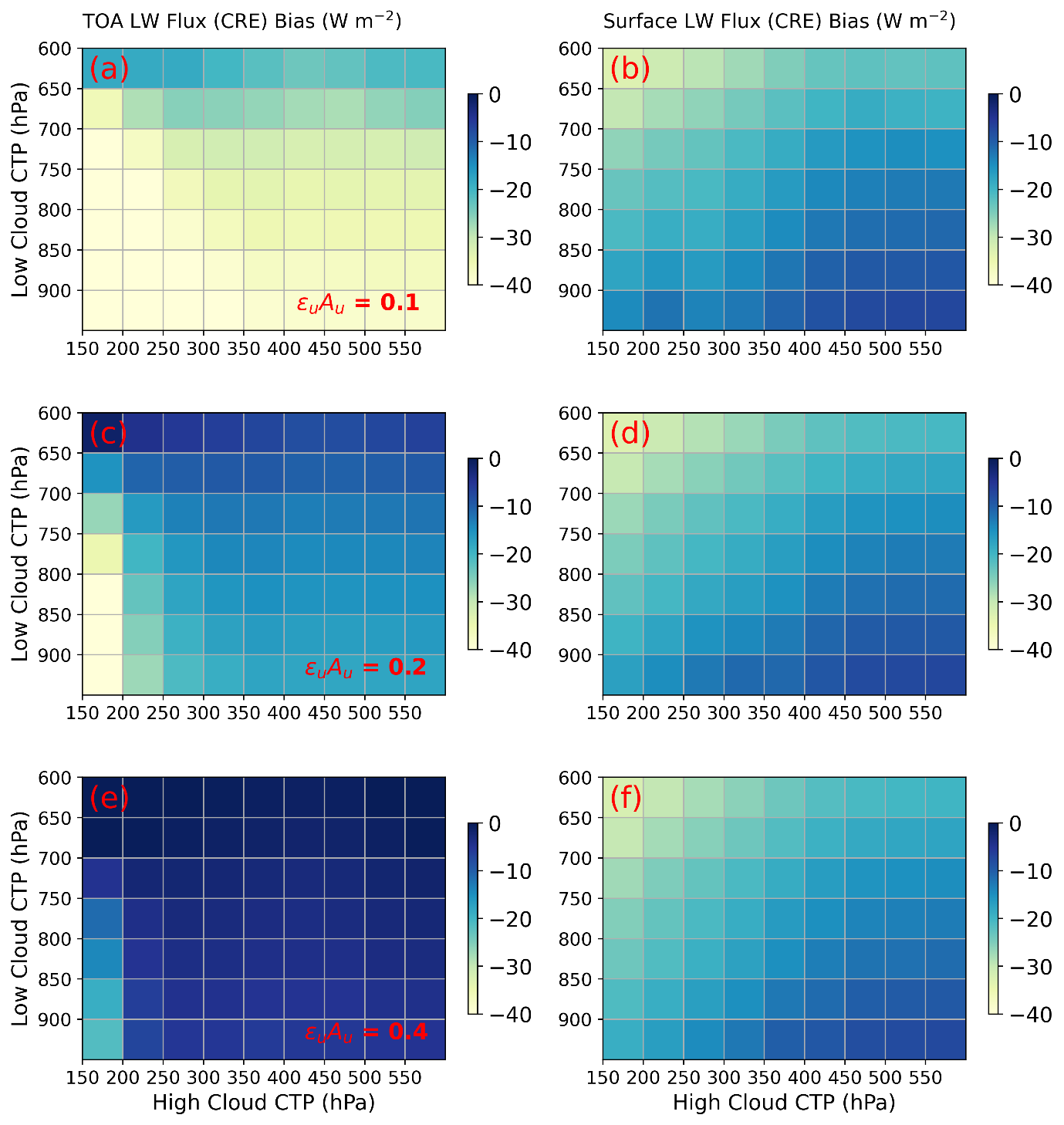
As noted in Section 1, the vertical distribution of cloud properties controls the vertical variation of cloud radiative effect (CRE); defined as the difference in cloudy and clear sky upwelling radiative fluxes. As a result, the accuracies of the MM\_CTH method in determining macrophysical and optical cloud properties in 2-layered systems are expected to improve our estimates of modeled radiative fluxes (and hence, estimates of CRE) for such systems.

Let us note that the outgoing longwave (LW) CRE at TOA for high clouds (presumably majority ice-phase) is large due to their cold cloud-top temperatures. Low clouds exhibit strong negative CRE at TOA due to their typically larger optical depths and warmer cloud-top temperatures (LW). However, when these clouds coexist in multi-layered situations, the interactive radiative effects between high and low clouds also influence the CRE (in addition to the individual effects of the layers). To study such effects, the true macrophysical and optical properties of the high layer must be better known. The often-erroneous retrievals of high cloud properties in multi-layered scenes from satellite sensors, when taken at face-value in radiative flux and Earth’s energy budget calculations could lead to spurious estimates of LW (and shortwave) CRE. Moreover, since the observed cloud properties themselves might not be consistent with observed radiative fluxes, they cannot act as trustworthy benchmarks to tune cloud properties in models. Here, we attempt to derive a very simplistic understanding of the nature of one such error, by estimating the impact of a single-layer CO2-slicing CTP and effective emissivity bias on simulated TOA and surface LW CRE. The impact of single-layer retrievals are ostensibly significant for shortwave (SW) CRE as well. However, we do not present SW impacts as such results would be strongly dependent on multiple factors beyond the properties of the cloud layers, such as ice/water single-scattering properties and sun-satellite geometry, which would be beyond the scope of concise explanation.

To estimate the LW impact of single-layered retrievals, we use the values of CTP overestimations (and corresponding overestimations of effective emissivity) for Band 36/35 (the more widely applied solution) from Figure 1. ‘True’ LW CRE is defined as the difference between cloudy and clear-sky LW atmospheric radiative fluxes using ‘true’ parameters for high and low cloud properties (that we pre-define). To estimate this quantity, we account for the combined radiative effect of both the ice and liquid clouds present in a scene. However, after the application of a single-layered CO2-slicing retrieval, we retrieve a single ice cloud layer at a lower altitude, with an optical depth that is contributed by both layers (Eq 10). We use this retrieved single-layer CTP and emissivity to define the macrophysical and optical properties of the scene and calculate an ‘observed’ LW CRE. By ‘observed’, we mean the flux computed by a radiative transfer model using the retrieved cloud properties rather than based on direct flux observations. ‘True’ minus ‘observed’ LW CRE gives us LW CRE bias. We calculate LW CRE bias at the surface and TOA. The variation of surface and TOA LW CRE bias is shown in Figure 5. Further details of the radiative transfer simulations are in Section II of Supplemental Materials.

The left panels of Fig. 6 shows that TOA LW CRE bias is sensitive to both the cloud macrophysics and high-cloud emissivity. The absolute value of the bias decreases with increasing optical depth of the upper cloud layer. As noted in Section 4.1.2, applying a 1-layered CO2-slicing retrieval on a 2-layered system results in overestimations in CTP, and for the upper-cloud layer. Since the retrieved cloud is nearly opaque in the infrared, the TOA LW CRE bias varies with the extent of gaseous emission (especially water vapor emission) above the opaque cloud layer. For any given value of cirrus amount, the LW CRE bias hence depends on the relative positions of the two cloud layers. An optically thin cirrus results in a 1-layered CO2-slicing CTP retrieval than an optically thicker cirrus at the same cloud altitude. As a result, when one moves down the left panels of Fig. 6, for progressively thicker cirrus at the top, the above-cloud emission is reduced, leading to a lower absolute values of TOA LW CRE bias.

While the surface LW CRE bias (right panels of Figure 6) is noticeably independent of high cloud optical depth (or, effective emissivity), it is dependent on the relative altitudes of the two layers. Surface LW CRE is dominated by near-surface emission, so subtler changes due to high cloud properties at colder temperatures is largely irrelevant and the surface CRE bias is largely a function of the low-cloud base. So, in this case, too, the relative positions of the high and low clouds, as well as the optical properties of these layers, play a crucial role in determining CRE bias.

These results are a simple analysis of the inconsistencies that can arise between observed radiative fluxes and retrieved cloud properties when the single-layer assumption is assumed. Our improved retrieval algorithm, MM\_CTH which retrieves high-accuracy cirrus CTP (Section 4), will provide improvements in radiative fluxes estimated using models that are of a similar order of magnitude (~10 W m-2)to the CRE biases calculated here. These improvements to modeled radiative fluxeswill be helpful when estimating the surface and atmospheric radiation budgets [e.g., Kato et al. (2018)], and will also provide a set of cloud properties that is more consistent with TOA radiation budget, thereby providing a stricter benchmark for the evaluation of climate models*.*

*Figure 6. Variation of top-of-atmosphere (left panels) and surface (right panels) LW Flux (CRE) bias (W m-2) with variations in high and low CTP, due to a single-layered CO2-slicing retrieval on a 2-layer scene. The atmosphere and surface properties are set up similar to Figure 1. CRE bias is defined as true minus modeled LW CRE. High Cloud Effective Emissivity is taken to be 0.1 (top panels), 0.2 (middle panels) and 0.4 (bottom panels).*

1. ***Conclusions***

Thin cirrus cloud overlying low clouds constitute >80% of multi-layered clouds globally (multi-layered clouds themselves constitute ~30% of all cloud cover). The underestimation by MODIS of the heights of thin cirrus overlying a thicker low cloud has been identified as the source of the largest errors in the climate record of CTH from Terra-based spectroradiometers (Mitra et al., 2021; Naud et al., 2007). In this study, we have developed an algorithm to retrieve accurate high-cloud properties for 2-layered cloud systems, named the *MISR-MODIS Fusion Product for Cloud-Top Height (MM\_CTH)*. MM\_CTH used a modified version of the standard MODIS CO2-slicing algorithm (of the Collection 6.1 MOD06 product) for the retrieval of CTP and emissivity of thin ice clouds, using accurate MISR low-cloud CTH retrievals as an input to account for the presence of the lower cloud in multi-layer scenes. Using collocated ISS-CATS as a reference, we validate the MM\_CTH retrievals to find ~90% reduction in cirrus CTP bias over MOD06. This improvement to CTP accuracy propagates to ~75% improvements in cirrus CTH and effective amount over standard MOD06. The MM\_CTH algorithm also allows us to retrieve lidar-like distributions of high cloud macrophysics (Figure 2b and 2d) and optical properties (Figure 3) in 2-layer cloud systems from passive sensors. The statistics from the validation of CO2-slicing CTP, CTH and thermal IR (against CATS), and the distributions of CATS, MOD06 and MM\_CTH CTP, CTH and are summarized in Table 1, below.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Data  Source | Mean Errors (with respect to CATS) | | | Net Distribution for High Clouds | | |
| **CTP (hPa)** | **CTH (km)** |  | **CTP (hPa)** | **CTH (km)** |  |
| MOD06 | 65±85 | -1.6±2.3 | 0.4±0.3 | 300±85 | 9.7±2.3 | 0.5±0.3 |
| MM\_CTH | 5±80 | -0.4±2.4 | 0.1±0.2 | 235±70 | 11.2±2.0 | 0.2±0.2 |
| CATS | N/A | N/A | N/A | 225±80 | 11.7±2.5 | 0.1±0.2 |

Table 1. Summary of mean errors in CO2-slicing CTP, CTH and effective emissivity for MOD06 and MM\_CTH with respect to CATS and the mean value of the distributions of CTP, CTH and effective emissivity from MOD06, MM\_CTH and CATS.

We performed an error budget analysis using CATS high cloud retrievals as reference. CATS high cloud retrievals, ERA5 modeling error estimates, and estimates of MISR CTH and MISR, MODIS, CATS geo-collocation errors from Mitra et al., (2021) are used to model the systematic and random sources of CTP error, which are then compared against empirical estimates of errors (from comparison with CATS). 78% of all observed errors were found to be within theoretical limits (i.e., 95% CI), when non-opacity of low-cloud properties (stemming primarily from sub-pixel clouds) are neglected. However, when low-cloud non-blackness is accounted for, 88% of observed MM\_CTH error estimates fall within the limits of 95% CI, providing a near closure of the MM\_CTH error budget. While beyond the scope of the current study, these results illustrate the necessity of sub-km cloud masks capable of detecting the presence of small clouds. MISR has 275 m channels and multi-angular views that are hypothetically capable of detecting the presence of such clouds, if the existing cloud mask algorithms, such as the Stereoscopically Derived Cloud Mask (SDCM) (Diner et al., 1999) is improved for sub-km detection. If such sub-1 km cloud masks do become available in the future, then their higher resolution cloud fraction estimates can be easily integrated into our algorithm to improve the accuracy of MM\_CTH retrievals even further.

We also demonstrate that this improvement is highly relevant in studies dealing with Earth’s radiative budget, as the largest CO2-slicing errors are associated with 2-layered systems topped by optically thin cirrus (Figure 1), which also happen to be the most prevalent, globally. In these 2-layered cloud systems, our results demonstrate that using MM\_CTH retrievals rather than the standard single-layer assumption retrievals improve estimates of modeled atmospheric fluxes (demonstrated for TOA and surface LW CRE in Figure 6) by ~5 to 45 W m-2, depending on the 2-layered properties. Thus, our algorithm could provide a climatology of CTH and high-cloud optical properties that is more consistent with the fluctuations in the Earth’s radiation budget than corresponding estimates from standard MOD06 retrievals for multi-layered scenes.

Although this current study is concerned with the pixel-level MM\_CTH algorithm and its validation and error budget analysis, we would like to stress its future importance to broader climate science, especially in leveraging the 22-year-long stable Terra record to study long-term climate-scale cloud responses, especially for high cloud populations. Of the many cloud responses to anthropogenic forcing predicted by models, the highest confidence is associated with rising CTHs (Boucher et al. 2013). Rising CTH is predicted to be the first signal of forced change that will emerge above natural variability (Chepfer et al., 2014; Winker et al., 2017). For example, simulations of a uniform 21st century 4K warming had predicted the increase in high cloud amounts by ~5-15%, along with ~25 m/year increase in mean tropical high CTH (Chepfer et al., 2014). In fact, there have been non-significant detection of the expected rising patterns in global high cloud amounts from passive sensors (Aerenson et al., 2022; Norris et al., 2016). For confident detection of such trends, however, we need stable multi-decadal observations (subject to robust uncertainty analysis) of cloud vertical distribution, globally (Shea et al., 2017)*.* While active sensors capable of vertically resolving cloud layers like lidars might seem ideal, the emergence of such trends from lidars are thwarted by their short lifetimes and lack of swath coverage. Hence, multidecadal passive sensor records from stable-orbit satellites like Terra are still the best suited for such a task.

However, as demonstrated in Section 1, both stereoscopic and multi-spectral retrievals of cloud macrophysics suffer from issues of sensitivity to different cloud types and accuracy. MISR stereo misses a majority amount of cirrus in 2-layered cases. On the other hand, unless the cirrus is very thin (OD << 1), MODIS IR channels detect cirrus emission above the channels’ noise levels, but it is the restrictive choice of a 1-layer solution (in the MODIS forward model) that leads to the misrepresentation of cirrus properties, including its retrieved emissivity. Left unchecked, it would be difficult to impossible to decouple long-term changes in high cloud heights and emissivity from true changes in low cloud heights and amount using MODIS data alone. Similarly, it would be difficult to impossible to decouple long-term changes in low cloud heights and amounts from true changes in high cloud amount and optical depths from MISR.MM\_CTH is a means to tackle these problems as it is capable of providing lidar-like distributions of high cloud properties over a passive sensor swath (MISR swath) over the 22-year stable-orbit satellite record of Terra.

Unfortunately, the Terra platform has begun to drift in ECT in order to save fuel for a safe reentry for end-of-mission and with this drift, Terra’s stable climate record is at an end. Due to its unmatched stability and longevity, the Terra record will remain a unique climate record of cloud macro-physical and optical properties from space between 2000-2022. We are therefore left with the goal to ensure that the Terra record produces cloud products with well-characterized uncertainties for future studies on the Earth’s climate. Towards this goal, we strongly recommend that the pixel-level MM\_CTH algorithm introduced here be scaled to a fully operational product over the entire Terra record for public dissemination.

1. ***Acknowledgements, Software and Data Sources***

This research was supported under MISR project contract 147871 with the Jet Propulsion Laboratory, California Institute of Technology. Partial support from the NASA ACCESS program under contract NNX16AMO7A is also acknowledged. The Collection 6.1 MODIS Level 2 Clouds Software modified to create the MM\_CTH software was downloaded from the NASA Goddard Space Flight Center MODIS Adaptive Processing System (MODAPS) website (<https://modaps.modaps.eosdis.nasa.gov/software/MODIS/AM1M/PGE06/Collection61/>). The MISR data was downloaded from NASA Langley Research Center Atmospheric Sciences Data Center (<https://opendap.larc.nasa.gov/opendap/MISR/MIL2TCSP.001/>). The MODIS data were obtained through the Level 1 and Atmosphere Archive and Distribution System of NASA Goddard Space Flight Center (<https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/61/>). The CATS data was downloaded from the NASA Langley Research Center's ASDC DAAC (<https://opendap.larc.nasa.gov/opendap/CATS/>). We are thankful to the NASA MODIS, MISR and CATS teams for supplying the documentation and tools, including the MISR toolkit (<https://nasa.github.io/MISR-Toolkit/html/index.html>). All ERA5 Reanalyses are downloaded through the European Center for Medium-Range Weather Forecast (ECMWF) Climate Data Store (CDS) website (<https://cds.climate.copernicus.eu/cdsapp#!/home>). The geoid data used in this study was downloaded from the National Geospatial-Intelligence Agency (NGA) WGS84 website (<https://earth-info.nga.mil/index.php?dir=wgs84&action=wgs84>). Data were stored and computations were conducted on the computing infrastructure managed by the University of Illinois at Urbana-Champaign’s School of Earth, Society, and Environment (SESE).

1. ***References***

Aerenson, T., Marchand, R., Chepfer, H., & Medeiros, B. (2022). When Will MISR Detect Rising High Clouds? Journal of Geophysical Research: Atmospheres, 127(2), e2021JD035865. https://doi.org/10.1029/2021JD035865

Anderson, G. P., Clough, S. A., Kneizys, F. X., Chetwynd, J. H., & Shettle, E. P. (1986). AFGL Atmospheric Constituent Profiles (0.120km). AIR FORCE GEOPHYSICS LAB HANSCOM AFB MA. Retrieved from https://apps.dtic.mil/sti/citations/ADA175173

Baum, B.A., Uttal, T., Poellot, M., Ackerman, T. P., Alvarez, J. M., Intrieri, J., et al. (1995). Satellite Remote Sensing of Multiple Cloud Layers. https://doi.org/10.1175/1520-0469(1995)052<4210:SRSOMC>2.0.CO;2

Baum, Bryan A., & Spinhirne, J. D. (2000). Remote sensing of cloud properties using MODIS airborne simulator imagery during SUCCESS: 3. Cloud Overlap. Journal of Geophysical Research: Atmospheres, 105(D9), 11793–11804. https://doi.org/10.1029/1999JD901091

Baum, Bryan A., & Wielicki, B. A. (1994). Cirrus Cloud Retrieval Using Infrared Sounding Data: Multilevel Cloud Errors. Journal of Applied Meteorology and Climatology, 33(1), 107–117. https://doi.org/10.1175/1520-0450(1994)033<0107:CCRUIS>2.0.CO;2

Baum, Bryan A., Menzel, W. P., Frey, R. A., Tobin, D. C., Holz, R. E., Ackerman, S. A., et al. (2012). MODIS cloud-top property refinements for collection 6. Journal of Applied Meteorology and Climatology, 51(6), 1145–1163. https://doi.org/10.1175/JAMC-D-11-0203.1

Baum, Bryan A., Yang, P., Heymsfield, A. J., Bansemer, A., Cole, B. H., Merrelli, A., et al. (2014). Ice cloud single-scattering property models with the full phase matrix at wavelengths from 0.2 to 100µm. Journal of Quantitative Spectroscopy and Radiative Transfer, 146, 123–139. https://doi.org/10.1016/j.jqsrt.2014.02.029

Bouali, M., & Ladjal, S. (2011). Toward Optimal Destriping of MODIS Data Using a Unidirectional Variational Model. IEEE Transactions on Geoscience and Remote Sensing, 49(8), 2924–2935. https://doi.org/10.1109/TGRS.2011.2119399

Boucher, O., D. Randall, P. Artaxo, C. Bretherton, G. Feingold, P. Forster, V.-M. Kerminen, Y. Kondo, H. Liao, U. Lohmann, P. Rasch, S.K. Satheesh, S. Sherwood, B. Stevens and X.Y. Zhang, 2013: Clouds and Aerosols. In: Climate Change 2013: The Physical Sc, U. (2013). IPCC Ch 7: Clouds and Aerosols. https://doi.org/10.1017/CBO9781107415324.016

Cesana, G., Waliser, D. E., Henderson, D., L’Ecuyer, T. S., Jiang, X., & Li, J.-L. F. (2019). The Vertical Structure of Radiative Heating Rates: A Multimodel Evaluation Using A-Train Satellite Observations. Journal of Climate, 32(5), 1573–1590. https://doi.org/10.1175/JCLI-D-17-0136.1

Chang, F. L., & Li, Z. (2005). A new method for detection of cirrus overlapping water clouds and determination of their optical properties. Journal of the Atmospheric Sciences, 62(11), 3993–4009. https://doi.org/10.1175/JAS3578.1

Chepfer, H., Noel, V., Winker, D., & Chiriaco, M. (2014). Where and when will we observe cloud changes due to climate warming? Geophysical Research Letters, 41(23), 8387–8395. https://doi.org/10.1002/2014GL061792

Davies, R. (2019). ENSO and Teleconnections Observed Using MISR Cloud Height Anomalies. Remote Sensing, 11(1), 32. https://doi.org/10.3390/rs11010032

Derber, J. C., Parrish, D. F., & Lord, S. J. (1991). The New Global Operational Analysis System at the National Meteorological Center. Weather and Forecasting, 6(4), 538–547. https://doi.org/10.1175/1520-0434(1991)006<0538:TNGOAS>2.0.CO;2

Diner, D., Di Girolamo L. & Clothiaux, E. E. (1999) MISR: Level 1 Cloud Detection. Available at: https://eospso.gsfc.nasa.gov/sites/default/files/atbd/atbd-misr-06.pdf

Fu, Q., & Liou, K. N. (1992). On the Correlated k-Distribution Method for Radiative Transfer in Nonhomogeneous Atmospheres. Journal of the Atmospheric Sciences, 49(22), 2139–2156. https://doi.org/10.1175/1520-0469(1992)049<2139:OTCDMF>2.0.CO;2

Geiss, A., & Marchand, R. (2019). Cloud responses to climate variability over the extratropical oceans as observed by MISR and MODIS. Atmospheric Chemistry and Physics, 19(11), 7547–7565. https://doi.org/10.5194/acp-19-7547-2019

Graham, R. M., Hudson, S. R., & Maturilli, M. (2019). Improved Performance of ERA5 in Arctic Gateway Relative to Four Global Atmospheric Reanalyses. Geophysical Research Letters, 46(11), 6138–6147. https://doi.org/10.1029/2019GL082781

Haladay, T., & Stephens, G. (2009). Characteristics of tropical thin cirrus clouds deduced from joint CloudSat and CALIPSO observations. Journal of Geophysical Research Atmospheres, 114(8). https://doi.org/10.1029/2008JD010675

Hannon, S. E., Strow, L. L., & McMillan, W. W. (1996). Atmospheric infrared fast transmittance models: a comparison of two approaches. In Optical Spectroscopic Techniques and Instrumentation for Atmospheric and Space Research II (Vol. 2830, pp. 94–105). SPIE. https://doi.org/10.1117/12.256106

Hartmann, D. L., & Berry, S. E. (2017). The balanced radiative effect of tropical anvil clouds. Journal of Geophysical Research: Atmospheres, 122(9), 5003–5020. https://doi.org/10.1002/2017JD026460

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., et al. (2020). The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, 146(730), 1999–2049. https://doi.org/10.1002/qj.3803

Hong, Y., & Di Girolamo, L. (2020). Cloud phase characteristics over Southeast Asia from A-Train satellite observations. Atmospheric Chemistry and Physics, 20(13), 8267–8291. https://doi.org/10.5194/acp-20-8267-2020

Hu, Y. X., & Stamnes, K. (1993). An Accurate Parameterization of the Radiative Properties of Water Clouds Suitable for Use in Climate Models. Journal of Climate, 6(4), 728–742. https://doi.org/10.1175/1520-0442(1993)006<0728:AAPOTR>2.0.CO;2

Joiner, J., Vasilkov, A. P., Bhartia, P. K., Wind, G., Platnick, S., & Menzel, W. P. (2010). Detection of multi-layer and vertically-extended clouds using A-train sensors. Atmospheric Measurement Techniques, 3(1), 233–247. https://doi.org/10.5194/amt-3-233-2010

Kang, H., Choi, Y.-S., Hwang, J., & Kim, H.-S. (2020). On the cloud radiative effect for tropical high clouds overlying low clouds. Geoscience Letters, 7(1), 7. https://doi.org/10.1186/s40562-020-00156-6

Kato, S., Rose, F. G., Rutan, D. A., Thorsen, T. J., Loeb, N. G., Doelling, D. R., Huang, X., Smith, W. L., Su, W., and Ham, S. (2018). Surface Irradiances of Edition 4.0 Clouds and the Earth’s Radiant Energy System (CERES) Energy Balanced and Filled (EBAF) Data Product. Journal of Climate 31(11), 4501-4527. https://doi.org/10.1175/JCLI-D-17-0523.1

Kim, H.-S., Baum, B. A., & Choi, Y.-S. (2019). Use of spectral cloud emissivities and their related uncertainties to infer ice cloud boundaries: methodology and assessment using CALIPSO cloud products. Atmospheric Measurement Techniques, 12(9), 5039–5054. https://doi.org/10.5194/amt-12-5039-2019

King, M. D., Platnick, S., Menzel, W. P., Ackerman, S. A., & Hubanks, P. A. (2013). Spatial and temporal distribution of clouds observed by MODIS onboard the terra and aqua satellites. IEEE Transactions on Geoscience and Remote Sensing, 51(7), 3826–3852. https://doi.org/10.1109/TGRS.2012.2227333

L’Ecuyer, T. S., Hang, Y., Matus, A. V., & Wang, Z. (2019). Reassessing the Effect of Cloud Type on Earth’s Energy Balance in the Age of Active Spaceborne Observations. Part I: Top of Atmosphere and Surface. Journal of Climate, 32(19), 6197–6217. https://doi.org/10.1175/JCLI-D-18-0753.1

Lensky, I. M., & Rosenfeld, D. (2006). The time-space exchangeability of satellite retrieved relations between cloud top temperature and particle effective radius. Atmospheric Chemistry and Physics, 6(10), 2887–2894. https://doi.org/10.5194/acp-6-2887-2006

Li, J., Yi, Y., Minnis, P., Huang, J., Yan, H., Ma, Y., et al. (2011). Radiative effect differences between multi-layered and single-layer clouds derived from CERES, CALIPSO, and CloudSat data. Journal of Quantitative Spectroscopy and Radiative Transfer, 112(2), 361–375. https://doi.org/10.1016/j.jqsrt.2010.10.006

Li, Y., Thompson, D. W. J., & Bony, S. (2015). The Influence of Atmospheric Cloud Radiative Effects on the Large-Scale Atmospheric Circulation. Journal of Climate, 28(18), 7263–7278. https://doi.org/10.1175/JCLI-D-14-00825.1

Mace, G. G., & Berry, E. (2017, September 1). Using Active Remote Sensing to Evaluate Cloud-Climate Feedbacks: a Review and a Look to the Future. Current Climate Change Reports. Springer. https://doi.org/10.1007/s40641-017-0067-9

Marchand, R., Ackerman, T., Smyth, M., & Rossow, W. B. (2010). A review of cloud top height and optical depth histograms from MISR, ISCCP, and MODIS. Journal of Geophysical Research: Atmospheres, 115(D16). https://doi.org/10.1029/2009JD013422

Marchant, B., Platnick, S., Meyer, K., Arnold, G. T., & Riedi, J. (2016). MODIS Collection 6 shortwave-derived cloud phase classification algorithm and comparisons with CALIOP. Atmospheric Measurement Techniques, 9(4), 1587–1599. https://doi.org/10.5194/amt-9-1587-2016

Marchant, B., Platnick, S., Meyer, K., & Wind, G. (2020). Evaluation of the MODIS Collection 6 multilayer cloud detection algorithm through comparisons with CloudSat Cloud Profiling Radar and CALIPSO CALIOP products. Atmospheric Measurement Techniques, 13(6), 3263–3275. https://doi.org/10.5194/amt-13-3263-2020

Mayer, B., & Kylling, A. (2005). Technical note: The libRadtran software package for radiative transfer calculations - description and examples of use. Atmospheric Chemistry and Physics, 5(7), 1855–1877. https://doi.org/10.5194/acp-5-1855-2005

McFarlane, N. (2011). Parameterizations: representing key processes in climate models without resolving them. WIREs Climate Change, 2(4), 482–497. https://doi.org/10.1002/wcc.122

McFarlane, S. A., Mather, J. H., Ackerman, T. P., & Liu, Z. (2008). Effect of clouds on the calculated vertical distribution of shortwave absorption in the tropics. Journal of Geophysical Research: Atmospheres, 113(D18). https://doi.org/10.1029/2008JD009791

McGill, M. J., Yorks, J. E., Scott, V. S., Kupchock, A. W., & Selmer, P. A. (2015). The Cloud-Aerosol Transport System (CATS): a technology demonstration on the International Space Station. In Lidar Remote Sensing for Environmental Monitoring XV (Vol. 9612, pp. 34–39). SPIE. https://doi.org/10.1117/12.2190841

Menzel, W. P., Frey, R. A., Zhang, H., Wylie, D. P., Moeller, C. C., Holz, R. E., et al. (2008). MODIS Global Cloud-Top Pressure and Amount Estimation: Algorithm Description and Results. Journal of Applied Meteorology and Climatology, 47(4), 1175–1198. https://doi.org/10.1175/2007JAMC1705.1

Menzel, W. P., R. A. Frey, and B. A. Baum (2015), Cloud Top Properties and Cloud Phase Algorithm Theoretical Basis Document Collection 006 Update. Available at https://atmosphere-imager.gsfc.nasa.gov/sites/default/files/ModAtmo/MOD06-ATBD\_2015\_05\_01\_1.pdf

Minnis, P., Alvarez, J. M., Sassen, K., Young, D. F., & Grund, C. J. (1990). The 27–28 October 1986 FIRE IFO Cirrus Case Study: Cirrus Parameter Relationships Derived from Satellite and Lidar Data. Monthly Weather Review, 118(11), 2402–2425. https://doi.org/10.1175/1520-0493(1990)118<2402:TOFICC>2.0.CO;2

Mitra, A., Di Girolamo, L., Hong, Y., Zhan, Y., & Mueller, K. J. (2021). Assessment and Error Analysis of Terra-MODIS and MISR Cloud-Top Heights Through Comparison With ISS-CATS Lidar. Journal of Geophysical Research: Atmospheres, 126(9), e2020JD034281. https://doi.org/10.1029/2020JD034281

Naren Athreyas, K., Gunawan, E., & Tay, B. K. (2020). Estimation of vertical structure of latent heat generated in thunderstorms using CloudSat radar. Meteorological Applications, 27(2), e1902. https://doi.org/10.1002/met.1902

National Academies of Sciences, Engineering, and Medicine. 2018. Thriving on Our Changing Planet: A Decadal Strategy for Earth Observation from Space. Washington, DC: The National Academies Press. doi: https://doi.org/10.17226/24938

Naud, C., Muller, J.-P., Haeffelin, M., Morille, Y., & Delaval, A. (2004). Assessment of MISR and MODIS cloud top heights through inter-comparison with a back-scattering lidar at SIRTA. Geophysical Research Letters, 31(4). https://doi.org/10.1029/2003GL018976

Naud, C. M., Muller, J.-P., Clothiaux, E. E., Baum, B. A., & Menzel, W. P. (2005). Intercomparison of multiple years of MODIS, MISR and radar cloud-top heights. Annales Geophysicae, 23(7), 2415–2424. https://doi.org/10.5194/angeo-23-2415-2005

Naud, C. M., Baum, B. A., Pavolonis, M., Heidinger, A., Frey, R., & Zhang, H. (2007). Comparison of MISR and MODIS cloud-top heights in the presence of cloud overlap. Remote Sensing of Environment, 107(1), 200–210. https://doi.org/10.1016/j.rse.2006.09.030

Norris, J. R., Allen, R. J., Evan, A. T., Zelinka, M. D., O’Dell, C. W., & Klein, S. A. (2016). Evidence for climate change in the satellite cloud record. Nature, 536(7614), 72–75. https://doi.org/10.1038/nature18273

Oreopoulos, L., Cho, N., & Lee, D. (2017). New insights about cloud vertical structure from CloudSat and CALIPSO observations. Journal of Geophysical Research: Atmospheres, 122(17), 9280–9300. https://doi.org/10.1002/2017JD026629

Pavolonis, M. J., & Heidinger, A. K. (2004). Daytime Cloud Overlap Detection from AVHRR and VIIRS. Journal of Applied Meteorology, 43(5), 762–778. https://doi.org/10.1175/2099.1

Platnick, S., Meyer, K. G., King, M. D., Wind, G., Amarasinghe, N., Marchant, B., et al. (2017). The MODIS Cloud Optical and Microphysical Products: Collection 6 Updates and Examples From Terra and Aqua. IEEE Transactions on Geoscience and Remote Sensing, 55(1), 502–525. https://doi.org/10.1109/TGRS.2016.2610522

Prasad, A. A., & Davies, R. (2012). Detecting tropical thin cirrus using Multiangle Imaging SpectroRadiometer’s oblique cameras and modeled outgoing longwave radiation. Journal of Geophysical Research: Atmospheres, 117(D6). https://doi.org/10.1029/2011JD016798

Prasad, A. A., & Davies, R. (2013). An assessment of cirrus heights from MISR oblique stereo using ground-based radar and lidar at the Tropical Western Pacific ARM sites. Journal of Geophysical Research: Atmospheres, 118(11), 5588–5599. https://doi.org/10.1002/jgrd.50454

Rajapakshe, C., Zhang, Z., Yorks, J. E., Yu, H., Tan, Q., Meyer, K., et al. (2017). Seasonally Transported Aerosol Layers over Southeast Atlantic are Closer to Underlying Clouds than Previously Reported. Geophysical Research Letters, Volume 44(Iss 11), 5818–5825. https://doi.org/10.1002/2017gl073559

Reynolds, R. W., Smith, T. M., Liu, C., Chelton, D. B., Casey, K. S., & Schlax, M. G. (2007). Daily High-Resolution-Blended Analyses for Sea Surface Temperature. Journal of Climate, 20(22), 5473–5496. https://doi.org/10.1175/2007JCLI1824.1

Rossow, W. B., & Schiffer, R. A. (1999). Advances in Understanding Clouds from ISCCP. Bulletin of the American Meteorological Society, 80(11), 2261–2288. https://doi.org/10.1175/1520-0477(1999)080<2261:AIUCFI>2.0.CO;2

Sassen, K., Wang, Z., & Liu, D. (2008). Global distribution of cirrus clouds from CloudSat/Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) measurements. Journal of Geophysical Research: Atmospheres, 113(D8). https://doi.org/10.1029/2008JD009972

Seemann, S. W., Borbas, E. E., Knuteson, R. O., Stephenson, G. R., & Huang, H.-L. (2008). Development of a Global Infrared Land Surface Emissivity Database for Application to Clear Sky Sounding Retrievals from Multispectral Satellite Radiance Measurements. Journal of Applied Meteorology and Climatology, 47(1), 108–123. https://doi.org/10.1175/2007JAMC1590.1

Shea, Y. L., Wielicki, B. A., Sun-Mack, S., & Minnis, P. (2017). Quantifying the Dependence of Satellite Cloud Retrievals on Instrument Uncertainty. Journal of Climate, 30(17), 6959–6976. https://doi.org/10.1175/JCLI-D-16-0429.1

Tegtmeier, S., Anstey, J., Davis, S., Dragani, R., Harada, Y., Ivanciu, I., et al. (2020). Temperature and tropopause characteristics from reanalyses data in the tropical tropopause layer. Atmospheric Chemistry and Physics, 20(2), 753–770. https://doi.org/10.5194/acp-20-753-2020

Terai, C. R., Klein, S. A., & Zelinka, M. D. (2016). Constraining the low-cloud optical depth feedback at middle and high latitudes using satellite observations. Journal of Geophysical Research: Atmospheres, 121(16), 9696–9716. https://doi.org/10.1002/2016JD025233

Tetzner, D., Thomas, E., & Allen, C. (2019). A Validation of ERA5 Reanalysis Data in the Southern Antarctic Peninsula—Ellsworth Land Region, and Its Implications for Ice Core Studies. Geosciences, 9(7), 289. https://doi.org/10.3390/geosciences9070289

Voigt, A., Albern, N., Ceppi, P., Grise, K., Li, Y., & Medeiros, B. (2021). Clouds, radiation, and atmospheric circulation in the present-day climate and under climate change. WIREs Climate Change, 12(2), e694. https://doi.org/10.1002/wcc.694

Wang, L., & Dessler, A. E. (2006). Instantaneous cloud overlap statistics in the tropical area revealed by ICESat/GLAS data. Geophysical Research Letters, 33(15). https://doi.org/10.1029/2005GL024350

Weinreb, M. P., Xie, R., Lienesch, J. H., & D.S. Crosby. (1989). Destriping GOES images by matching empirical distribution functions. Remote Sensing of Environment, 29(2), 185–195. https://doi.org/10.1016/0034-4257(89)90026-6

Winker, D., Chepfer, H., Noel, V., & Cai, X. (2017). Observational Constraints on Cloud Feedbacks: The Role of Active Satellite Sensors. Surveys in Geophysics, 38(6), 1483–1508. https://doi.org/10.1007/s10712-017-9452-0

Yorks, J. E., McGill, M. J., Palm, S. P., Hlavka, D. L., Selmer, P. A., Nowottnick, E. P., et al. (2016). An overview of the CATS level 1 processing algorithms and data products. Geophysical Research Letters, 43(9), 4632–4639. https://doi.org/10.1002/2016GL068006

Yuan, T., & Oreopoulos, L. (2013). On the global character of overlap between low and high clouds. Geophysical Research Letters, 40(19), 5320–5326. https://doi.org/10.1002/grl.50871

Zhang, H., & Menzel, W. P. (2002). Improvement in thin cirrus retrievals using an emissivity-adjusted CO2 slicing algorithm. Journal of Geophysical Research: Atmospheres, 107(D17), AAC 2-1-AAC 2-11. https://doi.org/10.1029/2001JD001037

Zhao, G., & Di Girolamo, L. (2007). Statistics on the macrophysical properties of trade wind cumuli over the tropical western Atlantic. Journal of Geophysical Research: Atmospheres, 112(D10). https://doi.org/10.1029/2006JD007371

Zheng, Y., Rosenfeld, D., Zhu, Y., & Li, Z. (2019). Satellite-Based Estimation of Cloud Top Radiative Cooling Rate for Marine Stratocumulus. Geophysical Research Letters, 46(8), 4485–4494. https://doi.org/10.1029/2019GL082094

Zhou, C., Zelinka, M. D., Dessler, A. E., & Yang, P. (2013). An Analysis of the Short-Term Cloud Feedback Using MODIS Data. Journal of Climate, 26(13), 4803–4815. https://doi.org/10.1175/JCLI-D-12-00547.1

1. ***Supplementary Materials***

***I. Spatial distribution of collocated CATS, MISR and MODIS pixels where MODIS-MISR CTH difference > 1 km and MODIS employed CO2-slicing for Cloud-top Detection***

Chart

Description automatically generated

Supplementary Materials Figure 1. Spatial distribution of collocated CATS, Terra-MODIS and MISR pixels between 2015-17 (a) globally and (b) binned zonally.

***II. Details on Radiative Transfer Modeling to understand the LW CRE bias due to a 1-layered CO2-slicing (Section 5)***

To estimate broadband LW CRE we use radiative transfer simulations from the uvspec program in the version 2.0.4 libRadtran software package (Mayer & Kylling, 2005). The same climatological atmospheric and surface conditions are used as in Figure 1. Broadband LW fluxes are calculated in all cases between 4-100 µm using the DISORT radiative transfer solver with 16 streams. Molecular absorption is calculated using the ‘fu’ parameterization scheme (Fu & Liou, 1992). For the ‘True’ LW CRE we define both a low and a high cloud layer. The low cloud has a homogeneous cloud liquid water content of 0.5 g m-3 and particle effective radius (Re) of 10 µm with a geometric thickness of 500 m. Water cloud optical properties are calculated using the ‘hu’ scheme (Hu & Stamnes, 1993). For the high cloud, Re is fixed at 40 µm and geometric thickness at 100 m. This higher cloud is deliberately chosen to be geometrically thin to mimic the infinitesimally thin condition in a CO2-slicing forward model (Section 2).

The procedure for choosing the IWC of the high cloud is more complex. We prescribe the emissivity of the upper cloud layer in the MODIS 11 µm channel ( and a cloud fraction of unity. We convert the emissivity to an infrared optical depth ( at 11.2 µm (MODIS channel 31). We then use the ‘baum’ ice microphysical model (Baum et al., 2014) to calculate the required IWC from (Supplementary Materials Figure 2). To calculate the ‘observed’ LW CRE we use CTP and emissivity from our single-layered CO2-slicing algorithm to define a single ice cloud layer (500 m thick). The same conversion described above is used to define the IWC of this cloud. The Re of the retrieved cloud is assumed to be that of the upper cloud layer (40 µm). This procedure is repeated for different combinations of high CTP between 150-600 hPa and low cloud CTP between 600-1000 hPa for 3 values of high cloud effective emissivity (0.1, 0.2 and 0.4).

Chart, line chart

Description automatically generated

Supplementary Materials Figure 2. Variation of visible optical depth (τ) with ice-water content (IWC; g/m3) for a 250 m thick ice-cloud at 10 km, with effective radius of ice particles = 40 µm and in a tropical climatological atmospheric profile.