**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 overlapping lower cloud.
3. 86% of cloud-top pressure retrieval errors can be bound by theoretical estimates, resulting in a near-closure of error budget.

***Abstract***

Our longest, stable multi-decadal records of cloud-top pressure (CTP) from passive instruments such as the Moderate Resolution Imaging Spectroradiometer (MODIS) and Multi-Angle Imaging Spectroradiometer (MISR) on the Terra satellite provide insufficient knowledge of multi-layered cloud fields (~30% of all clouds) due to their use of single-layer assumptions. To improve our climate record of CTP, we develop a 2-layered retrieval that utilizes the complementary capabilities of MODIS and MISR to accurately retrieve the CTP of both upper and lower layers in 2-layer systems when the upper layer is optically thin (visible optical depth < 0.5), and the two layers are vertically separated by at least 1 km. MISR’s robust stereoscopy accurately retrieves the cloud-top height (CTH) of the lower cloud layer in these 2-layer systems. The MISR low-cloud height is provided as a lower boundary condition to a CO2-slicing retrieval from MODIS observations to retrieve accurate CTP of the upper-layer cloud.

Evaluation of the new 2-layered retrieval against the Cloud-Aerosol Transport System (CATS) lidar for multi-layered scenes demonstrates a mean bias and standard deviation of 5±80 hPa in CTP, which is a 90% reduction in CTP bias compared to the standard MODIS product (65±85 hPa). Below-cloud-base retrievals of top-layer heights drop from 38% in MODIS to 12% in our implementation. We developed an error model for the new retrieval accounting for systematic and random sources of error. 87% of all residuals of the 2-layered retrieval against the CATS lidar were found to be within the modelled 95% confidence intervals, indicating reasonable error closure. The 2-layered retrieval also provides upper cloud-layer emissivity and CTH with biases against CATS reduced by 75%, compared to MODIS. Distributions of retrieved CTH and visible optical depth from the improved retrieval are very similar to those of the CATS lidar. The improved cloud retrievals lead to more effective top-of-atmosphere and surface longwave flux closure using radiative transfer model simulations, with reduction in relative errors ranging between 5 to 45 Wm-2, depending on the relative position and optical properties of the layers.

This pixel-level experimental 2-layered fused product from Terra-MODIS and MISR can easily be scaled to an orbit-level product over the 22-year Terra record. Such a dataset can be hypothetically used to further our knowledge of 21st century climate, by refining our estimates of long-term variability in cloud amounts and providing us the first-of-its-kind climatology of 2-layered cloud systems 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). These cloud processes control and maintain the Earth’s circulation and precipitation (Y. Li et al., 2015; Voigt et al., 2021). Hence, clouds play an important role in the Earth’s climate system – 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 budget 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 these sub-grid cloud parameterizations and climate predictions (e.g., Zhou et al., 2013; Terai et al., 2016; Mace & Berry, 2017).

As such, research and technological advancements toward obtaining accurate, global observations of the horizontal and vertical distribution of cloud properties is crucial to improve the representation of cloud processes in climate models (NASEM 2018). The obvious choice to study the vertical variability of global cloud distribution is space-borne active sensors like lidars (e.g., CALIPSO lidar within NASA’s A-Train). However, although active sensors facilitate the much-needed detection of vertical variation of cloud properties, they lack swath information and are typically short-lived. The only record of cloud properties that provided us stable and multidecadal observations (features of a desirable climate record) from a single satellite platform came 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 of Terra’s ECT makes it a unique climate record, as 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 such as CO2-slicing and 11µm brightness temperature difference tests to determine CTH from cloud-top pressure or temperature (Baum et al., 2012; Menzel et al., 2008). The choice of MODIS’s retrieval method is based on the cloud phase and instrument noise.

However, as in all legacy passive sensors, 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 cloud overlap (Sassen et al., 2008; Joiner et al., 2010; Yuan & Oreopoulos, 2013; Li et al., 2015; Oreopoulos et al., 2017; Hong & Di Girolamo, 2020). The single-layer assumption, coupled with the lack of an active sensor, means that accuracy of CTH retrievals for multi-layered clouds from Terra is poor. Net cloud radiative effect strongly mirrors the degree of 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). By far the most dominant multi-layered cloud regime is a 2-layered system with thin cirrus overlaying water clouds, followed by thin cirrus overlying mixed-phase clouds (Wang & Dessler, 2006; Oreopoulos et al., 2017; Hong and Di Girolamo 2020). As such, one can argue that accurate estimation of cloud overlap parameters (e.g., frequency of overlap or the properties of individual layers) by a space-based radiometric sensor is strongly tied to its ability to retrieve the presence and properties of cirrus within a scene.

A-Train observations have shown that the distribution of thin cirrus (detected by lidar but not by radar) have a mean cloud OD of 0.1±0.1 (Haladay & Stephens, 2009). ~60% of such cirrus in the tropics between ±20º latitude have at least one lower cloud layer present (Haladay & Stephens, 2009). The statistics of cirrus OD distribution from Terra-MODIS is markedly different from the A-Train record (King et al., 2013), with the Terra-MODIS suggesting much greater mean cirrus OD than A-train active sensors. As such, if the Terra records are to reach full maturity as climate records, attention must be paid to improving the detection of cirrus, especially under cloud overlap. Such improved estimates of vertical variability of cloud heights from Terra can not only impact studies of long-term climate variability (Davies, 2019; Geiss & Marchand, 2019), but also studies of cloud microphysics (Lensky & Rosenfeld, 2006), radiative balance (Hartmann & Berry, 2017; Zheng et al., 2019), and even numerical weather prediction.

The path to improving the Terra record relies on exploiting the independent information contained within the MODIS and MISR CTH techniques. Numerous validation studies using ground and space-based active sensors have shown that the presence of multi-layered cloud leads to the most significant disagreements in retrieved CTH between these two sensors (Naud et al., 2004; Naud et al., 2005, 2007; Marchand et al., 2010; Mitra et al., 2021). As we will see, this indicates a degree of independence of the two techniques that can be exploited to retrieve accurate CTHs in many 2-layered cloud systems. CTH errors in multi-layered cloud regimes have been most recently and comprehensively studied for the Terra record 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. Biases of this sort 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 OD < ~0.4. However, MISR failed to detect the higher layer >80% of the time (typically when upper-layer OD > 0.4). This is due to the greater contribution of the optically thicker, more textured lower-level 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. 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 proposed fusion algorithm is the first of its kind among passive sensors. Previous attempts to mitigate the effects of multi-layering have largely focused on single-instrument solutions. A number of techniques have focused on just the identification of the presence of multi-layering. These have included a few bispectral (Baum et al., 1995), multi-sensor (Baum & Spinhirne, 2000) and multi-spectral (Pavolonis & Heidinger, 2004) techniques, with even the latest MODIS cloud products employing a water-vapor absorption band (0.94 µm; insensitive to thin cirrus) to detect the presence of cloud overlap (Baum et al., 2012). A few methods (Chang & Li, 2005; Kim et al., 2019), however, have been suggested to retrieve the CTH and/or optical properties of each individual layer of clouds in the multi-layered system. However, those techniques were fraught with significant uncertainties themselves, as the low-cloud information had to be approximately assumed from multi-spectral data or from nearby pixels. Improvements have also been proposed to the operational MISR algorithms, to improve their sensitivity to the presence of cirrus by utilizing MISR’s most oblique views (Prasad & Davies, 2012, 2013). However, by utilizing a multi-instrument fusion approach, we can enforce homogeneity in the climate record, resolving the inter-instrument disagreements and make best use of the strengths of each.

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 observations from the CATS lidar, along with an error budget analysis for the 2-layered CO2-slicing. 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; Menzel et al., 2008), as used in MODIS, 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 clear-sky IR radiance, (neglecting scattering) observed by a satellite sensor band with central wavelength λ, 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 , P is pressure. (λ, P) denotes the atmospheric transmittance between *P* and the satellite. For a completely opaque cloud the effective emissivity, which is the product of the cloud fraction () and the cloud layer emissivity (), is unity. In this case, the nadir radiance observed by the satellite sensor, , 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 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 bands (say Band 1 and Band 2) in the 15µm CO2-absorption band, we have , which from Eq. 3, leads to

where, and are the central wavelengths of Bands 1 and 2, respectively. 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, which results in a CTP solution that is larger than the true when adopting a single-layer strategy. 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 in a modification to Eq. 4. Comparing Eq. 3 and Eq. 6, and assuming the lower cloud to be black [i.e., , we estimate this emission as the second term in Eq. 6:

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:

In this study, we apply the 2-layer adjustment on scenes where MODIS minus MISR CTH difference > 1 km, to ensure that the adjustments are applied to truly distinct layers of clouds.

1. ***Methodology***

Section 3.1 briefly describes the datasets used in this study to both implement and validate the CO2-slicing algorithms presented in Section 2. Moreover, salient points of the implementation of both 1-layer and 2-layer CO2-slicing have also been highlighted in Section 3.2.

***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, however, 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 at 1, 5, 10, 50, 100, 250, 350, 450, 500, 650, 750, 850, 900, 950 and 1000 hPa are taken and interpolated using a linear interpolation between the multi-level atmospheric reanalysis and the logarithm of pressure, to arrive at the atmospheric state at the 101 pressure levels that are employed by the MOD06 algorithm. Surface pressures, temperatures (2m temperature over land and sea-surface temperature over oceans) and 2m dewpoint temperature (to calculate surface moisture) are also used from ERA5 reanalysis, 4 times daily, to set up the model surface.

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. 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, restricted to scenes where CATS detected *at least* 2 layers. Upon further conditions being imposed (CO2-slicing-only scenes and MODIS-MISR CTH difference > 1 km), it is found that 95% of all scenes in the remaining dataset are likely 2-layered (92% of which includes CATS signal being attenuated at the second layer). The remaining 5% of pixels show attenuation in a near-surface third cloud layer. The study is conducted on a dataset constituting 2790 pixels taken from 501 independent scenes (i.e., unique MISR and MODIS granules and CATS orbits), hence ~6 samples per scene (Supplemental Figure 1).

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

where, equals the thermal IR optical depth (). The constant = 2.56 for ice clouds (Minnis et al., 1990). Estimates of visible optical depth () of the topmost cloud layer for a given scene 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 lidar estimates of high cloud are converted to infrared effective emissivity (, assuming = 1) for validation, using Eq. 10. MODIS 1 km-resolution CTP, CTH, effective emissivity () and visible optical depth () are also used in validation, taken from the MOD06 product.

Since validating the new technique is a central goal of this study, our analysis is restricted to pixels where MISR, MODIS and CATS made coincident observations of multi-layered clouds and where MODIS applied CO2-slicing for cloud-top height retrieval as documented in Mitra et al. (2021). This means, however, restricting the scope of the validation of this new technique to between the extreme latitudes traversed by the ISS orbit (±52º in either hemisphere).

***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 and wrapped it in Python. Salient features of the operational code and the modifications for our implementation are hereby discussed.

The primary goal of computation in this algorithm is to simulate 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 thermal IR 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 make sure that this condition is met, the MOD06 cloud phase detection algorithm is run ahead of the cloud-top algorithm and CO2-slicing technique is applied only on such scenes where phase detection flags an ice cloud (11.2 µm brightness temperature technique is applied for water, mixed and uncertain phase detections).

Comparisons of Aqua-MODIS cloud phase with CLOUDSAT/CALIPSO data had previously shown >90% agreement in ice-clouds for multiple surface types for single-phase clouds (Marchant et al., 2016; Platnick et al., 2017). For multi-layered clouds with different phase, Marchant et al. (2020) showed ~30% detection of ice-phase in ice-over-liquid type overlap and ~20% ice-phase detection for ice-over-mixed phase clouds, underlying the difficulty of detecting the presence of ice phase when it overlays a cloud of another phase. This, unfortunately, means even with the promised improvements of our technique, a sizable portion of global overlap cannot be studied by it. However, since our goal is to improve the accuracy of the CO2-slicing technique (even at the cost of reduced implementation of the technique), we choose to restrict the implementation of the CO2-slicing technique (similar to that of the operational MODIS algorithm) to only scenes with a confident detection of ice phase. 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.

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

To obtain solutions for CTP and emissivity, Equation 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 thermal IR emissivity or effective cloud amount.

The standard MOD06 product 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 validation.

To conduct a sanity check for the fidelity of our implementation, 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 ±1σ difference in CTP between our implementation and MOD06 to be -5±30 hPa. For these scenes, the mean CTP bias for MOD06 CTP is 20±30 hPa, whereas for our implementation, the mean CTP bias is 15±35 hPa. This provides confidence in the soundness of our implementation, while also underscoring the fact that moving from GDAS to ERA5 reanalysis has very little impact on the success of a single-layer CO2-slicing retrieval.

Chart, scatter chart

Description automatically generated

Figure 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 (1100 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).

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 procedure is highly idealized, neglecting all errors in the forward model, but provides an indication of the systematic biases that result from the strict assumption of a single layer. We perform retrievals on the synthetic two-layered systems for a climatological tropical atmosphere for different values of and , as shown in Figure 1. We calculate the overestimations of CTP above for four effective cloud amounts between 0.05-0.75, for each of the spectral band pairs that are used by Terra MODIS (36/35 on the left panels, and 35/33 on the right panels). 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 cloud over a low cloud that is at a sufficient height for the surface. It is unsurprising that the 35/33 band pair is more susceptible to the presence of low clouds because in going from 13.3 to 14.2 µm, there is a drastic reduction in the amount of near-surface radiation that reaches the satellite sensor, due to increased absorption from atmospheric 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, and hence in both those 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). To be noted the Figure 10 of Menzel et al. (2015) was an effective representation of CTP error by an unspecified CO2-slicing band-pair. As a result, Figure 1 is the first depiction in the literature of MODIS CO2-slicing overlap bias, broken down by band-pair.

Based on these findings, our bias-correction (Equations 8 and 9) is most suited and meaningful for well-separated layers only (as noted in Section 2).

***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 both band pairs – 36/35 and 35/33 – are recorded. A best solution is also chosen using the aforementioned “top-down” method. If no legitimate solution is found, it is a no-retrieval. It is found that 305 (~11%) pixels are no-retrievals. This is largely due to the presence of radiance artifacts such as striping, that may be dealt with in later implementations through established procedures of MODIS radiance de-striping (Bouali & Ladjal, 2011; Weinreb et al., 1989). In the current study, such bad radiance pixels are removed from all analyses.

All 2485 valid CTP retrievals are also converted to CTHs, using ERA5 geopotential heights. All such retrievals are also used to estimate effective cloud amounts (using Eq. 9). MOD06 cloud amounts are also noted for comparison. Following Eq. 10, effective cloud amounts are converted to visible OD (), assuming To be noted, the new estimates for and are estimates of the high cloud optical properties, in contrast to the corresponding MOD06 retrievals, which represents vertically integrated optical properties for all clouds in the atmospheric column.

This aforementioned modification to the CO2-slicing is rooted in physical theory and makes use of Terra’s unique design, and hence, allows us to improve MODIS upper-layer CTP/CTH and emissivity, provided the layer is optically thin for MISR to retrieve CTH of the lower cloud [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, emissivity and OD as the **MISR-MODIS 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***

Chart, histogram

Description automatically generatedAs 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 the 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 distribution differences of high cloud CTP/CTH from the 3 techniques (MOD06, MM\_CTH and CATS) on the right panels. The mean bias and SD 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.

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 dashed lines in each color represents the mean value of the quantities whose distributions are in that same color.

We reiterate that MOD06 and MM\_CTH use different reanalyses products as ancillary inputs. While we chose not to do a direct comparison of our results using GDAS output and ERA5 reanalysis, we do note that using the ERA5 reanalysis with a single-layered assumption (for multi-layered scenes) such as in MOD06, results in a bias and SD of 55±90 hPa and -1.4±2.4 km, in CTP and CTH, respectively, representing a 15% improvement over MOD06. Based on these findings and the comparison between MOD06 and 1-layer MM\_CTH (Section 3.2.1), we can say that the change in reanalysis product only introduces minute changes in CO2-slicing accuracy. The significant improvement in accuracy is, thus, primarily due to the better representation of the physics of 2-cloud-layer radiative transfer.

This aforementioned 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. It was noted in Mitra et al. (2021) that for 42% of cases of multi-layered clouds with a thin high layer, MODIS CTH lies below the geometric extent of the high cloud layer (i.e., lower than CATS cloud-layer base). In our shortened dataset (due to additional constraints), such cases were 38%. The application of the 2-layered solution in MM\_CTH reduces the number of such 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 (~10% of each distribution) where MM\_CTH appears to overestimate the value of CATS CTH by > 4 km (i.e., underestimate the value of 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 find a mean difference of -0.5±0.5 km. This number is close to MISR’s CTH accuracy for low clouds (Mitra et al., 2021). This suggests that, in these scenes, MODIS retrieved cirrus heights, but CATS detected low clouds. 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.

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

Unlike cloud-top property variables such as CTP and CTH, we do not have an unbiased (or nearly unbiased) estimate for cloud effective amount ( to directly compare against. CATS is converted to CATS by inverting Eq. 10. Even though this is not an unbiased estimate of true , by acknowledging that the MOD06 is a vertically averaged value of effective cloud emissivity in the atmospheric column, one can reasonably expect the CATS to be a closer estimate of true emissivity, even with the strict assumption that . Based on that assumption, we note that the CO2-slicing bias in reduces from 0.4±0.3 in MOD06 to 0.1±0.3 for MM\_CTH, a ~75% reduction in the overestimation of high cloud emissivity, that is unsurprising given the improved estimate of CTP.

Chart, line chart

Description automatically generatedThis leads to corresponding improvements in the distributions of high cloud and (derived from estimates of , using Eq. 10), that are plotted in Figure 4. As with CTP/CTH, the distributions from MM\_CTH closely align with the CATS distribution, whereas the difference between the MOD06 and MM\_CTH distributions are even more stark. This is due to the fact that fundamentally, the MOD06 and MM\_CTH optical properties represent entirely different physical entities, and not just a biased estimate (like MOD06 CTP/CTH). Whereas the MOD06 emissivity and OD are abstractions of the vertically averaged or integrated optical properties of the entire atmospheric column, respectively, the MM\_CTH optical properties are, in fact, now an estimate of the optical properties of just the thin high cloud layer.

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 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. A detailed discussion of the CTP error budget follows in Section 4.2.

*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.*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| 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 |

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

Here, we shall account for the various sources of systematic and random errors in MM\_CTH CTP and investigate the effects of known and suspected sources of error in our product. The sources of error we shall consider include:

1. the covariance of modelling errors in temperature and specific humidity in the ERA5 reanalysis,
2. the inherent noise in detected radiances from the MODIS spectral bands,
3. the observational uncertainty in MISR low-cloud stereo heights,
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. breakdown of the black assumption for the low clouds, and,
8. the effect of uncertainty in surface emissivity.

Of these parameters, 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, in the following section these last two sources will be dealt with in a different manner to the other sources.

Our goal is to compare the distribution of observed and theoretical estimates of these errors in order to figure out how much of the observed error distributions are theoretically bound. To do that, we need to calculate theoretical estimates of systematic and random errors for a grid of possible values of variables on which the CO2-slicing retrieval depends, in the form of error matrices. The error matrices (one for each of the 5 climate zones of Section 3.1) have the general 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. We calculate CTP using the MM\_CTH technique for:

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 OD (0.25 intervals between 0.25 and 2.5)

i.e., for a total of 4800 cases over both band-pairs. The range of values of the high cloud properties are based on the known distributions of those properties from CATS, whereas the range of values for is based on MISR low-cloud CTH distribution (in units of pressure).

We further note that low cloud CTP, atmospheric profiles, and instrument radiances are not exactly measured or known. Rather, minute perturbations in these quantities can ostensibly impact our estimates of error. As a result, we perturb these 3 quantities to derive 200 different realizations of each of the 4800 cases mentioned before. We perturb the 3 quantities as follows.

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 surface pressure, z is the altitude of the level and H is the scale height of the atmosphere, taken to be 8.5 km.

For every instance of , we draw 200 samples of by biasing the value with the pressure-equivalent of MISR CTH – 230 m (using the form for *P(z)*, given above) and then perturbing the resultant CTP by 200 random samples drawn from a normal distribution given by µ=0, σ =

1. **ERA5 Reanalysis Error:** To estimate the error-covariances of the ERA5 temperature and moisture profiles, we used the 10 ERA5 ensemble members (Hersbach et al., 2020), that is 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 a day from each month of 2016 and calculated flow-dependent perturbations by subtracting each ensemble member from the ensemble mean. We then grouped perturbations across all positions and days within each of 5 climate regimes: Northern Hemisphere Summer and Winter, Tropical, Southern Hemisphere Summer and Winter (refer to Section 3.1). Here, we estimated the error-correlations between the 37 different pressure levels of the profiles of temperature and moisture reanalysis, neglecting all error-correlations between adjacent columns. Horizontal error correlations are relevant for the aggregation of pixel retrievals, not for individual pixel-level uncertainties.

Given the error-covariance matrix in each of the five climate regimes, we propagated the resulting errors to errors in CTP through Monte Carlo sampling. Specifically, we drew 200 perturbed (‘error’) profiles of temperature and moisture, from the estimated error-covariance matrix assuming Gaussian statistics. Upon comparing against empirical estimates of ERA5 uncertainty (Graham et al., 2019), we further found the ensemble to be accurately dispersive with respect to specific humidity, but under-dispersive in the matter of temperature uncertainty, by a factor ranging between 4-6, depending on pressure level. To correct this discrepancy, temperature profile perturbations are inflated by a constant value of 5, for all pressure levels.

1. **Instrument Noise**: We introduce perturbations to the calculated TOA radiances, by means of 200 random samples drawn from a normal distribution with µ=0, σ = 1 W m‑2 (equating the radiance threshold levels of the 15 µm CO2-slicing channels with noise).

To model the error due to a finite cloud depth, we modify the gas-only model (described in Section 3.2) for clear-sky radiative transfer to include cloud by modifying the transmission profile. We simply prescribe a cloud optical depth, cloud-top pressure, and cloud bottom pressure (based on our choices of in the error matrices) and assume that cloud extinction is homogeneously distributed in pressure between these two levels. We verify that our implementation is correct using the analytic solution for an isothermal and non-scattering atmosphere. The model is necessarily inaccurate for non-black surfaces as only a single direction/stream is modeled. However, for our purposes, we can now 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 an infinitesimally thin high cloud assumption.

After all these steps that were meant to factor in all the major sources of systematic and random errors in the radiative transfer, we run the MM\_CTH algorithm over all such possible realizations. We record the bias and standard deviation over the 200 perturbed instances, for each of the 4800 combinations of , for each of the 5 climate zones. Theoretical estimate of bias and random error for an observed pixel-level error is drawn from the combination of all these parameters that is closest to the conditions observed over that pixel.

To account for further sources of random uncertainty, we estimated the uncertainty in CTP introduced by the process of geo-collocation of MODIS and CATS pixels. Mitra et al. (2021) noted an uncertainty of 900 m in CTH due to the geo-collocation of MODIS and CATS pixels for CATS-retrieved high clouds (CATS CTH > 5 km). Using the equation to propagate height errors to pressure errors given earlier, we could calculate the 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 in our calculations, which can be denoted by , and will be numerically equal to the grid-spacing of 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, that are accounted by the standard deviation estimates from .

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 low cloud and surface effects to be the reason behind the existence of 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 partially 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, the effect of surface emissivity is overlooked.

Chart, scatter chart

Description automatically generatedTo investigate the effects of low-cloud properties, we first establish that myriad low-cloud effects such as the brokenness of the cumuliform clouds, heterogeneity of low cloud optical properties within the pixel or semi-transparency of the low clouds will all manifest themselves in our model as a breakdown of the opaque low cloud condition (i.e., . To properly understand this effect, 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 4800 cases, for each of the 5 climate zones mentioned above. Effective IR emissivity is then converted to cloud OD at the low cloud level, 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 effective cloud amount and MODIS CO2-slicing band pair, are noted and are plotted 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.

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.

We note here that the expected dominant effect of low-cloud heterogeneity probably arises from trade-wind cumuli, whose coverage is extensive over the area in study. Zhao & Di Girolamo, (2007) noted a peak cloud-effective diameter of ~450 m for such clouds, which approximately means an effective cloud fraction () = 0.16, for a 1 km pixel. We extract the equivalent bias in CTP from Figure 4 for 0.16 (taking the mean bias from both band-pairs, weighted by their relative frequency of usage, in our dataset), and this bias is termed as , and we note that its effect is additive on the overall bias in our dataset. Hence, we redefine bias-corrected errors to now mean , and on doing so, find 87% of all errors to lie within 95% confidence interval. With only 8% outside of confidence limits, we can say that a near-closure of the MM\_CTH CO2-slicing error budget has been achieved.

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

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 clear and cloudy sky fluxes. As a result, the ability of the MM\_CTH method in determining the vertical variation of cloud properties in 2-layered systems in general, and better estimates of high cloud properties in particular, will also improve our ability to simulate the radiative impact of such systems.

Let us note that high clouds (presumably majority ice-phase) exhibit small shortwave CRE. However, their outgoing longwave (LW) CRE is large due to their cold cloud-top temperatures. On the one hand, low clouds exhibit strong negative CRE due to their typically larger OD and also considerably 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), which is impossible to ascertain unless the true macrophysical and optical properties of the high layer are 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/SW CRE. Here, we attempt to derive a very simplistic understanding of the nature of such an error, by estimating the impact of a single-layer CO2-slicing CTP and effective emissivity bias on the TOA and surface LW CRE.

Towards this end, we make use of the values of CTP overestimations for Band 36/35 (the more widely applied solution) from Figure 1 (noting corresponding overestimations in effective emissivity). ‘True’ LW CRE can then be defined as the difference between all-sky minus clear-sky LW fluxes at any altitude, when taking into consideration the combined effect of both the ice and liquid clouds 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. We use the retrieved 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 model using the retrieved cloud properties rather than based on direct flux observations. True minus observed LW CRE gives us an estimate of LW CRE bias.

Chart, treemap chart

Description automatically generatedTo estimate the 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 Figure 5. 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).

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 in the atmosphere. 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.

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 assume that cloud fraction is 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 the retrieved CTP and emissivity to define a single ice cloud layer for the calculation of the fluxes using uvspec. The same conversion described above is used to define the IWC of this cloud. The ground truth Re is assumed to be that of the ice cloud. 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). The variation of LW CRE across all these instances is shown in Figure 5.

We notice that TOA LW CRE bias (left panels of Figure 5) is both sensitive to cloud macrophysics and high-cloud emissivity with CRE bias < -40 W m-2 for = 0.1. The absolute value of the bias decreases with increasing optical depth of the higher cloud. Here, it needs to be noted that the resultant emissivity and OD of the ‘false’ single-layer cloud is high enough ( > 2) to make the layer effectively opaque in the infrared (nearly similar to the low cloud in the ‘true’ case). As a result, the driving factor behind the bias is the change in the extent of gaseous emission (especially water vapor emission) above the opaque cloud layer, in both cases. A thin high cloud layer results in an effective cloud layer that is lower in altitude than that arising due to a thicker high cloud, and as a result, there is more above-cloud emission, which, in turn, leads to greater absolute value of LW CRE bias. On the other hand, while surface LW CRE bias (right panels of Figure 5) is noticeably independent of high cloud optical depth (or, effective emissivity), there is, however, a dependence 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.

The results of this subsection represent a very simplistic model of the problem and is merely meant to be a qualitative assessment of the radiative impact of using biased single-layer CO2-slicing CTP/emissivity to estimate longwave fluxes for multi-layered scenes. It is meant to further underscore the importance of the MM\_CTH algorithm (Section 2) as the basis for a more robust climate record of clouds over the Terra record.

1. ***Conclusions***

In this study, we have developed an algorithm to retrieve robust and accurate high-cloud properties for 2-layered cloud systems. These systems had been previously 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). The retrieval algorithm, named the *MISR-MODIS Product for Cloud-Top Height (MM\_CTH),* relies on the assumption that the MISR-retrieved low cloud stereo height is opaque in the infrared. With this assumption, the standard MODIS CO2-slicing algorithm (of the Collection 6.1 MOD06 product) for the retrieval of CTP and emissivity of thin ice clouds is modified to account for the presence of the lower cloud in multi-layer scenes. The MM\_CTH algorithm identifies multi-layered clouds as pixels with MODIS – MISR CTH difference > 1 km, based on the findings of Mitra et al., (2021). MM\_CTH also differs from the MOD06 implementation in its usage of ERA5 reanalysis in the setting up of the model atmosphere and surface, as opposed to the usage of GDAS in MOD06. This modification is implemented on all collocated pixels with multi-layered systems (based on the aforementioned definition) from MODIS, MISR and the CATS lidar over the period of CATS operation (2015-2017), and where the MOD06 algorithm had previously used CO2-slicing for its CTP detection. MM\_CTH retrievals are validated against the CATS record, and its error characteristics are contrasted against MOD06.

The 2-layered correction reduces the CTP bias in multi-layered cases from 65±85 hPa to 5±80 hPa, a ~90% reduction. The robustness of other CO2-slicing retrievals (CTH and emissivity) is dependent on the robustness of the CTP retrieval. Hence, the improvements to CTP accuracy propagates to improvements in accuracy for CO2-slicing high-cloud heights (1.6±2.3 km in MOD06 to 0.4±2.4 km in MM\_CTH) and emissivity (0.4±0.3 in MOD06 to 0.1±0.2 in MM\_CTH). The MM\_CTH algorithm further allows us to retrieve lidar-like distributions of high cloud macrophysics (Figure 2b and 2d) and optical properties such as optical depth (Figure 3) in 2-layer cloud systems from passive sensors, through synergistic usage of MODIS and MISR and appropriate microphysical assumptions (Eq. 10).

We performed a robust error analysis using CATS high cloud retrievals as reference. CATS high cloud retrievals, ERA5 modeling error estimates, and the findings of Mitra et al., (2021) are used to model the systematic and random sources of CTP error, and then compared against empirical estimates of errors. 78% of all observed errors were found to be within theoretical limits (i.e., 95% CI), when the effect of low-cloud properties are neglected. However, when we account for low-cloud non-blackness (stemming primarily from sub-pixel clouds), we are able to further constrain the MM\_CTH error distribution (Figure 4). Using the most probable cloud diameter of the most common sub-pixel low clouds (i.e., trade cumuli) from Zhao & Di Girolamo (2007), we recalculated the bounds of theoretical error. In this new paradigm, 87% of observed error estimates were found to be bounded by 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 for the MODIS and MISR cloud masks to move from their current ~1 km resolutions to 250 m, since 250 m channels are available in both. If such sub-1 km cloud masks do become available in the future, then they can be easily integrated into our algorithm to improve accuracy 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. Our results demonstrate that using MM\_CTH retrievals can improve estimates of modeled atmospheric fluxes (demonstrated for TOA and surface LW fluxes, in Figure 5) by 5 to 45 W m-2 over using single-layered retrievals, depending on the 2-layered properties. While not shown in this study, SW radiative effects from misinterpreting 2-layered systems as a single-layer will also likely be significant (Kang et al., 2020). 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.

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, estimates from 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). For confident detection of these small predicted trends, we need stable multi-decadal observations (subject to robust uncertainty analysis) of cloud vertical distribution, globally (Shea et al., 2017)*.* However, the of emergence of such trends from active sensors are thwarted by the short durations and lack of swath coverage.

A record of lidar-like distribution of high cloud properties from a passive sensor in space (e.g., MM\_CTH) signifies the best of both conditions required in a stable climate dataset – spatial coverage and accuracy. 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). 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.Therefore, to extend the utility of the Terra record for climate research, this problem must be fixed.

Unfortunately, the Terra platform has begun to drift in ECT in order to save fuel for a safe reentry for end-of-mission. By June 2022 it will have reached an ECT of 10:15 AM, thus surpassing the 10:30 AM ± 15-minute ECT stability requirement of the mission (it actually maintained a 10:30 AM ± 1-minute ECT from 2002 to 2021). However, with Terra’s drift in ECT, its stable climate record is at an end. With no similar long-term satellite mission planned, the Terra record will remain an unmatched climate record of cloud macro-physical and optical properties for at least three more decades. We are therefore left with the goal to ensure that the Terra record produces cloud products with well-characterized uncertainties. Towards this goal, the pixel-level MM\_CTH algorithm introduced here must be scaled to a fully operational product over the entire Terra record.

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

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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

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

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

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]

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

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***

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.

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.