Determination and analysis of DSCOVR-EIPC satellite-retrieved radiance from cloud geometric and optical properties

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1. Abstract

Using simulations and numerical fitting, this work sought to describe the satellite-retrieved radiance of clouds as a function of their thermodynamic and optical properties. Subsequently, this understanding can be used in a look-up-table to determine the properties of clouds imaged by the EPIC sensor in the NASA DSCOVR satellite. In this study, background oxygen absorption was modeled in a radiative transfer model and convolved with EPIC filter functions for two absorption-reference pairs for Oxygen A- and B-band. This absorption profile was established as the primary vertical coordinate in this study, leveraging the similarity principle to allow for intercomparison of cloud cases. Cloud cases were taken from a modeled dataset from WRF-SBM which calculated a variety of stratiform and convective measurements. Radiance was simulated for the oxygen A- and B-narrowbands and their reference bands using the Discrete Ordinates Radiative Transfer Model from a wide array of atmospheric parameters and determined the best way to functionally describe their behavior. The resulting non-linear fitting model incorporates solar zenith angle, surface albedo, cloud geometry, and cloud optical depth to describe a strong fit for the log-ratio of each absorption/reference pair. The Oxygen A-band model S-value was 0.037 for log-ratio values ranging from 0.3 through 3.0, and the Oxygen B-band model S-value was 0.023 for log-ratio values ranging from 0.3 through 1.3.
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2. Overview

2.1 Importance of Cloud Remote Sensing

Clouds are one of the largest sources of error in climate models with one of the lowest levels of categorical understanding (Myhre et al. 2013). Cloud cover is a main contributor to Earth’s radiation budget, responsible for scattering incoming solar radiation and blocking or re-radiating outgoing terrestrial radiation, distinctions of which are due to their optical and geometric properties. Changes in the height and thickness of a cloud have drastically different radiative effects across the electromagnetic spectrum, and their evolution is complex and difficult to model even with restrictive temporal and spatial parameters. Optical depth, by its definition, determines how much solar radiation is allowed through a medium, so clouds with high optical depth block most of an incident beam and those with low optical depth are largely transparent to it. Subsequently, geometrically thick clouds, with significantly higher water content, are much stronger insulators of thermal radiation than geometrically thinner ones, blocking it from escaping the atmosphere. But cloud height also factors into the radiation budget. The Stephan-Boltzmann equation for radiation of a body, gray- or otherwise, describes a relationship with temperature raised to the 4th power, and cloud top temperatures decrease significantly with increased heights. So with even a small increase in cloud top height and, subsequently, decreased cloud top temperature, the decreased outgoing radiation is significant. As such, accurate determination of cloud properties goes beyond weather prediction further to being vital for calculating and modeling their radiative impacts.

Considering the global expanse of cloud cover, satellite retrieval continues to be the most effective method for cloud observations, though not without its own plague of persistent issues. Both active and passive sensors suffer from signal intrusions from things such as surface effects and atmospheric constituents not of interest with shared spectral depen-
encies. Additionally, satellite orbits and instrumentation capabilities have to compromise between coverage and resolution and, as such, are often limited in their ability to sufficiently capture global cloud movement and evolution. The trade-off between spatial and temporal coarseness and coverage for many cloud-sensing-capable satellites is a barrier that can be hard to overcome, as clouds exist on a wide range of time and spatial scales, from minutes to days and from micro to synoptic and regional. Observations which take advantage of cloud absorption and reflection suffer from a variety of errors inherent with signal attenuation and incomplete extinction in the form of photon penetration, a concept discussed in section

2.2 Underlying Concepts

2.2.1 Current Approaches: non-A- or B-band

In pursuit of better understanding of cloud extent and behavior, a number of remote sensing detection methods have been developed. Similar in concept and application are CO$_2$ slicing (Menzel et al. 1983) and lidar (Weisz et al. 2007). CO$_2$ slicing approaches cloud top height detection in a similar form to this work’s use of ratios of oxygen absorption but, instead, uses ratios of absorption by CO$_2$. One of the main detriments of this method, as discussed in O’Brien, D. M., Mitchell (1992), is, since the point of comparison must be sufficiently close together on the electromagnetic spectrum, retrieval suffers from significant instrument noise that can, at times, mask the signal of interest.

Lidar is a highly accurate method of retrieving cloud top heights in certain situations, as shown in the comparisons in Weisz et al. (2007), but is not without its own share of difficulties. Lidar is able to penetrate thin clouds and can identify even broken edges of clouds, but is blocked by the first optically thick cloud encountered, eliminating any further information below the thick layer. Additionally, as it functions as an active sensor, cost of manufacture and maintenance can be prohibitive for broad coverage and use. The CALIOP lidar on board the CALIPSO satellite, a member of the A-Train and thus able to co-locate
retrievals with a suite of supplementary data from adjacent satellites, presents a worthy compromise for such an active sensor, but suffers from temporal and spatial gaps which can prove difficult to handle when searching for a particular area of interest. Inquiry is limited to that which falls directly beneath the 90m CALIOP footprint (CNES - Centre National D’Etudes Spatiales 2016).

2.2.2 Current A- and B-band Approaches

An early but exhaustive approach to cloud height retrievals through oxygen A-band methods was taken by Fischer and Grassl (Fischer and Grassl 1991), involving taking the ratio of radiance within the A-band (761nm) with a point far outside it (755nm). Of particular note is the broad cloud properties considered, with cloud optical depths ranging from 0.1 – 197 and cloud top heights from 0.1 – 10km. Accuracy of near 50m for cloud top height retrievals were found for the forward model look-up-table procedure. Of note is the discussion on the bearing of vertical distribution of liquid water content on retrievals, demonstrating sensitivity to this variable. Addressing this concept was attempted, with an in-depth treatment given in Section 6.

O’Brien, D. M., Mitchell (1992) approach the A-band ratio method with multiple data points within the A-band and one out-of-band reference point. Accuracy in this model is stated at 5hPa and cites instrument noise as the largest contributor to error. Additionally, it was found that errors in the retrieval were largely insensitive to photon pathlength, though this can be brought into greater context as the study only considered clouds which were optically thick (cloud optical depths greater than 30). Though optically thin clouds are ignored in this method, surface albedo ($A_{sfc}$) effects were considered and found to have similarly little impact on retrieval error when compared to instrument effects.

Calculation of cloud boundary pressures for the POLarization and Directionality of Earth’s Reflectances (POLDER) instrument also leverages A-band absorption, though the
ratio of band information is leveraged to account for surface albedo effects (Vanbauce et al. 2003). The measurements considered (765nm and 670nm) take into account an absorptive case and a fully non-absorptive case to calculate the fraction of photons directly reflected by the cloud, allowing the remainder to be calculated as reflected by the surface and leading to a “corrected cloud pressure” $P_{cloud}$. With such surface correction, this model accounts for cloud optical depths greater than 3.5, a significant encapsulation of optically thin clouds.

A semi-analytical model, developed by Rozanov (2004) and leveraged for the operational algorithm for the SCIAMACHY instrument, also uses oxygen A-band absorption and ratios between strong and weak absorption cases. It is based on the asymptotic theory of the radiative transfer equation for optically thick media, thus restricting applicable cloud optical depths to those falling within 10 – 50. Error for this retrieval is stated to be within 20m, though surface effects were eliminated with an $A_{sfc}$ value of 0.0 and the model geometry assumes a single cloud layer with homogenous vertical distribution of cloud liquid water content (LWC). A linear function was chosen to model upward radiances as behavior was approximately linear across the variable range. This is intuitive considering the assumption of asymptotic behavior and restriction of optical variables.

2.2.3 DSCOVR EPIC

With the new capabilities of the Earth Polychromatic Imaging Camera (EPIC) on-board the NASA Deep-Space Climate Observatory (DSCOVR) satellite, it is possible to make hourly observations of clouds over the entire sun-lit side of the earth, an unparalleled combination of coverage and temporal resolution. Applying a look-up table (LUT) for cloud top heights, the end result of this study, and combining such measurements with other EPIC cloud products will produce operationally-ready cloud measurements for use in forecasting and climate models alike. Ideally, products such as this will reduce the need for parameterizing cloud input for such models and provide much-needed reduction in error.
2.2.4 Theory

Single scattering involves a single non-absorbing extinction interaction between a photon and a scatterer, whereas multiple scattering involves the subsequent continued scattering of the initially-scattered photon, illustrated in Figure 2.1. Single scattering cases revolve around optically extremely thin mediums, or cases with strong absorption, both of which reduce the likelihood of more than one scattering event, while multiple scattering results from optically thick and strongly scattering media. As complex, varying media, both single and multiple scattering need to be considered for cloud interactions. While single scattering can be represented by a probability density function, multiple scattering takes on a random distribution of cases. Complicating this further is the possibility of multiple atmospheric "pathways" through which a photon can travel and then be retrieved by the sensor. Yang et al. (Yang et al. 2013) describe six discrete such pathways as a simple schematic: 1) reflection by Rayleigh regime in a layer below a cloud; 2) reflection by a Rayleigh regime above a cloud; 3) reflection by the interim cloud layer; 4) transmission through Rayleigh-cloud-Rayleigh atmosphere to be reflected by the surface; 5) reflection by Rayleigh-only atmosphere with no cloud; and transmission through Rayleigh layer to reflect at the surface. Fortunately, a statistical representation of average distance traveled throughout a medium, described here as mean photon pathlength, is sufficient and alleviates the need to know the exact scattering paths of each photon. Following similar work from Min and Harrison (1999), a restatement of the Bouger-Lambert-Beer Law for multiple scattering can be written as Equation 2.1.

\[
\frac{I(\lambda)}{I_0(\lambda)} = \int_0^\infty \exp^{-\chi(\lambda)l} P(l)dl
\]  

(2.1)

Oxygen is a well-mixed atmospheric gas, demonstrated by constituent profiles presented in the AFGL compilation report (Anderson et al. 1986), with strong absorption peaks at 763nm and 687nm, referred to as oxygen A-band and B-band absorption. Narrow
bands encompassing these two absorption peaks have significantly little absorption contribution from non-oxygen sources and, thus, allow the establishment of oxygen absorption as a vertical coordinate, crucial for the calculation and comparison of photon pathlength. Working in the "oxygen optical depth-space" $\tau_{O_2}$ allows for atmospheric-independent calculation and comparison of cloud geometry. This can be most easily shown in the rephrasing of the derivation for the source function in Zege et al. (1991), shown in Equation 2.2. Citing the Law of Radiant Energy Conservation for Scattering Media, we can introduce the relationship $\vec{\tau} = \epsilon \vec{R}$, a "dimensionless optical radius-vector" what is more easily understood as "optical depth", and make a substitution in the source function, B, shown in Equations 2.3 and ultimately 2.4. This substitution shows as the light field is independent of $\epsilon$, two different scattering media, with the same single scattering albedo and phase functions, have the same radiance at a given $\tau_{O_2}$. Leveraging oxygen absorption as a vertical atmospheric coordinate extends to the retrieval of cloud top height by extension of the equivalence theorem; scattering and absorption for clouds and other atmospheric constituents are known, so signal attenuation in these bands can be attributed to distance traveled through the atmosphere above the cloud top surface.

\[
\frac{dI}{dl} = -\epsilon I(\vec{R}, \vec{n}) + B_{full}(\vec{R}, \vec{n})
\]

(2.2)

\[
B'_{full}(\vec{\tau}, \vec{n}) = \frac{SSALB}{4\pi} \iiint_{4\pi} I(\vec{\tau}, \vec{n}) \times (\vec{n}, \vec{n}') \, d\vec{n}' + B(\vec{\tau}, \vec{n})
\]

(2.3)

\[
\frac{dI}{dl} = -\epsilon I(\vec{\tau}, \vec{n}) + B_{full}(\vec{\tau}, \vec{n})
\]

(2.4)

Clouds are not, however, perfect Lambertian reflectors and, even with such strong absorption cases such as oxygen in optically thick clouds, photons are not entirely and immediately attenuated at cloud incidence, demonstrated in Figure [refpic:photonpen]. Some
photons penetrate the upper portion of the attenuating cloud before being scattered, the distance traveled resulting in what is referred to as a photon penetration depth. This imperfect extinction case, exacerbated by more optically and/or geometrically thin clouds, results in an artificially lower cloud top height. Accounting for this effect is a vital component of this work, and previous success (Fischer and Grassl 1991; O’Brien, D. M., Mitchell 1992; Vanbauce et al. 2003; Rozanov 2004; Yang et al. 2013) has been found in leveraging the ratios of the main absorbing band and an adjacent, non-absorbing band. Cloud top heights have been shown to be a function of the ratio between absorbing and non-absorbing bands, so it follows we restate equation 2.5 as:

\[
\frac{I(\lambda_i)}{I(\lambda_0)} = \frac{I_0(\lambda_i)}{I_0(\lambda_0)} \int_0^\infty \exp^{-\chi(\lambda)l} P(l) dl \quad (2.5)
\]

Finally, we supply a function \(f(<l>)\) to describe mean photon pathlength:

\[
\frac{I(\lambda_i)}{I(\lambda_0)} \approx \frac{I_0(\lambda_i)}{I_0(\lambda_0)} \exp^{-f_i(<l>)} \quad (2.6)
\]

Equation 2.6 guides the non-linear fitting function in the following sensitivity study with an expansion of the function of mean pathlength described in terms of cloud and atmospheric properties and view geometry.
Figure 2.1: An illustration of single and multiple scattering of incident radiation.

Figure 2.2: An illustration of photon penetration of a cloud top surface and subsequent retrieval of artificially lowered cloud top height.
3. EPIC

3.1 Filters and Geometry

The Deep-Space Climate Observatory (DSCOVR) satellite is a recently launched observation platform which orbits in the first Sun-Earth Lagrange point (L1), 1.5 million km from the Earth, and has a suite of instruments oriented Earth- and sunward (Eckman 2014). Of the Earthward instruments, this work is concerned with the Earth Polychromatic Imaging Camera (EPIC) sensor, an instrument with continuous view of the entire sunlit hemisphere. This, coupled with a sampling horizontal spatial resolution of 17 km and multiple narrowband spectral channels, provides a distinctly new dataset for the global spatial extent and evolution of clouds. Of the 10 narrowband channels, two absorption and reference pairs, 780nm versus 779.5nm and 680nm versus 687.75nm, for oxygen A- and B-band behavior are leveraged. Data from this sensor is retrieved at a rate near once per hour for each spectral band. While original proposals for cloud top height products assumed a dark surface, this work shows a product can be made available for surfaces of varied brightness. Perturbations of orbit between 2-7 degrees, due to the six-month Lissajous orbit of the satellite required for continuous residence in the L1-position, but these changes are known and can be corrected for.

Of particular interest for forward radiative transfer model calculations is the geometry of DSCOVR with respect to the sun and Earth. As the satellite is aligned with the sun with respect to a point on the Earth surface, accounting for previously described fluctuations, there exist some convenient geometric cancellations within the derivation of the radiative transfer equation. View angle and solar zenith angle (radiation source) are assumed equal and, thus, can cancel each other in ratios and simplify functional dependence terms. As described in Section 5 this has major bearing on the forward model radiative transfer func-
tion. By similar token, the azimuthal component of the radiative transfer equation is only a constant; with the zenith angle for radiation source and view, azimuth is taken purely from series expansion of scattering.

A horizontal resolution of 17 km also has some interesting impacts on the resulting radiative transfer equation; this somewhat coarse grid excludes consideration of small-scale, transient, or broken clouds as individual contributors. Instead, we adopt the single-plane assumption for this derivation in that multiple layered scatterers and absorbers in an atmospheric column, here defined as an EPIC pixel, can be represented by a single plane of equivalent optical depth. This is a situation in which the establishment of $\tau_O$ as a vertical coordinate is particularly useful in that it allows an easy conversion to such an equivalent plane. For ease of calculation we go further in assuming this single plane acts as a Lambertian surface in that it scatters incident radiation isotropically, allowing for the scalar azimuthal effect in the aforementioned series expansion.

3.2 Algorithm Concept

The initial goal of this study was to create a forward radiative transfer calculation to define EPIC-retrieved reflectance as a function of cloud and atmospheric parameters through the creation of a look-up table (LUT). This presents an opportunity for an accurate but fast calculation of cloud height without the need for complex calculations for every data-packet download as the radiative transfer equation has been preemptively solved for each retrieval. Operational use follows with the "looking-up" of cloud information for a given pixel's retrieved reflectance, or reflectance ratio. Described in further detail is the development of the forward algorithm, including the incorporation of atmospheric inspecific calculation, satellite filter function, and modeled cloud cases as input for radiative transfer model calculation of satellite retrievals.
4. Fast Atmospheric Profile Conversion

4.1 Atmosphere Construction

Atmospheric molecular composition and distribution were created using a modified version of the 2008 High Resolution Transmission Molecular Absorption Database (HITRAN) (Harvard Center for Astrophysics 2015) for use with the Atmospheric and Environmental Research (AER) group LNFL module (Atmospheric and Environmental Science Research Center 2015). The HITRAN database was created using both direct observations and calculations using "quantum-mechanical solutions" to simulate atmospheric electromagnetic transmission and includes individual line parameters, or absorption cross-sections in areas of too-dense features, for 47 molecular species (Harvard Center for Astrophysics 2015). The line-file creation program, LNFL, uses a modified version of the HITRAN database, including the 2009 replacement for O$_2$ released in October 2012. While the HITRAN and AER line parameter databases have been updated since 2012, this version was used as none of the since-updated databases have had changes which affected the wavelength ranges for oxygen A- and B-band absorption, 760-782 and 670-690. Molecular column density for O$_2$ and temperature profiles are taken from the AFGL Tropical, Subarctic Winter, and U.S. 1976 Standard atmospheres (Anderson et al. 1986) and re-visualized in 4.1 and the geometric height, pressure, and temperature profile for the U.S. 1976 Standard is shown in 4.2.

The Line-by-Line Radiative Transfer Model (LBLRTM) created by AER (Clough and Iacono 1995) applied the processed line file to the atmospheric parameters and returned the resulting ambient atmosphere at a user-defined resolution. The LBLRTM applies AFGL atmospheric parameters to the line-by-line molecular transmission properties, as processed in the LNFL module. Output from this module can then be put onto any user-specified atmospheric resolution; here we have a two-part layering scheme defining the lower and
Figure 4.1: Comparison of AFGL atmospheres for Tropical, Subarctic Winter, and U.S. 1976 Standard atmospheric models

Figure 4.2: Expansion of AFGL U.S. 1976 Standard atmospheric model thermodynamic properties. This model was used through the duration of the project to be consistent with similar work for comparison.
upper atmosphere. Layers in the lower atmosphere are separated by a fixed 100 meter spacing up to 15 km, after which the layer spacing changes to linearly increase up to 93 km; this layering scheme was chosen to accentuate cloud features in the troposphere while preserving processing time by keeping the upper layers thicker. A visualization of this layering is shown in 4.3. Since the satellite retrieval encompasses atmospheric parameters of all types across the sun-lit hemisphere, it needs to be atmospheric-independent. A polynomial fitting of absorption over the three most disparate AFGL profiles; Tropical, Subarctic Winter, and the 1976 U.S. Standard Atmosphere; results in coefficients which can be applied to any atmospheric profile. Additionally, a temperature weighting scheme was applied, accounting for the temperature-dependence of molecular column density and its effect on molecular absorption. The efficacy of this temperature-weighted fit can be seen in 4.4 though the U.S. 1976 Standard atmosphere was used for the duration of the project.

4.2 Convolution with EPIC

The resulting atmospheric distribution of oxygen optical depth $\tau_{O_2}$ then must have applied the transmission function for the DSCOVR satellite, to account for the spectral lens reduction in signal. A straightforward convolution integration with the transmission function for the various absorption bands for oxygen was applied. The resolutions and ranges for the functions are described in 4.1 and were created with the overall absorption shape in mind, hence the irregular peaks and slight shifts of the curves seen in 4.2. The convolution integration involved a direct wavenumber-by-wavenumber scaling, followed by an integration across the spectral band, with the wavenumber-space computation satisfying the convolution restrictions of the Fourier transform. The result of this convolution is a single atmospheric profile for the entire band, absorption or reference, shown in Figures 4.6 and 4.7. Such a convolution accounts for both peak absorption lines and their ”wings”, structures which can be seen in 4.2 successfully capturing the entire absorption band. This step marks the beginning of the use of $\tau_{O_2}$ as the primary vertical coordinate in this workflow,
Figure 4.3: Layer thickness as a function of height for LBLRTM-layering scheme.

the importance of which is outlined in Section 2. Conversion back to geometric space is straightforward, however, and has behavior in geometric space in the U.S. 1976 Standard atmosphere as shown in 4.8.
Figure 4.4: Comparison of LBLRTM-calculated and temperature-weighted polynomial-fit atmosphere result.

Table 4.1: Summary of EPIC filter function resolutions, wavelength ranges, and the full-width at half maximum (FWHM) for each band.

<table>
<thead>
<tr>
<th>Band</th>
<th>Range (µm)</th>
<th>Resolution (µm)</th>
<th>FWHM</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-Band</td>
<td>760-766</td>
<td>0.02</td>
<td>1.00</td>
</tr>
<tr>
<td>A_{Ref}</td>
<td>776-782</td>
<td>0.02</td>
<td>1.82</td>
</tr>
<tr>
<td>B-Band</td>
<td>685-690</td>
<td>0.02</td>
<td>0.86</td>
</tr>
<tr>
<td>B_{Ref}</td>
<td>670-690</td>
<td>0.1</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Figure 4.5: Oxygen A- and B-band absorption spectrum with EPIC filter function overlays for main and reference bands.

Figure 4.6: Convolved $O_2$ optical depth profile as a function of geometric height.
Figure 4.7: Vertically integrated (TOA-down orientation) and layer O₂ optical depth profile as a function of atmospheric pressure.

Figure 4.8: Differential height as a function of geometric height for a given differential $\Delta \tau_{O₂}$.
5. Forward Radiative Transfer Model

5.1 Simulation

To ensure the cloud cases analyzed were indicative of a realistic atmosphere, data modeled using the Weather Research Forecasting Spectra-Bin Microphysics Model (WRF-SBM) were collected for use in satellite-retrieved reflectance simulation. The WRF-SBM model [NASA Goddard Space Flight Center 2017] was considered the most useful model for this kind of analysis because the SBM model, by design, does not prescribe most cloud microphysical parameters. Hydrometeors are allowed to develop naturally and the model explicitly calculates depositional and condensational growth, evaporation, sublimation, and other relevant droplet evolution characteristics. This dataset is represented by exclusively liquid clouds, and any cloud cases modeled that contained any ice content in the column were removed. Liquid water path returned from this modeled dataset was defined as the average value for the column and effective radius was used to describe the column particle size distribution. Cloud evolution was modeled for a period of 33 hours over an area of 1320 km$^2$ and sought to capture convective and stratiform behavior in the region highlighted in 5.1.

To improve computing time and to ensure outliers did not have undue sway over the modeling process, a subset of this modeled data was taken. The data were separated into categories by cloud top height, to guarantee a broad range of heights for sensitivity analysis, and then randomly-sampled points of 6% of one standard deviation above and below the mean for each cloud top height category were added to the final dataset. Success of this sampling in maintaining the character of the original data is shown in Figure 5.2 While the original WRF-SBM model run had 609,400 viable cases, 19,170 cases were finally input into the DISORT model run. While there can be some biases inherent in such an averaging, the
vast number of cases, spanning such a diverse range of optical and geometric properties, instills confidence in this assessment and ultimately result in a distribution of cloud optical depth seen in Figures 5.3 and 5.4. This broad range includes cloud bottom heights ranging from 0.1-6.5km, cloud top heights from 0.9-7.5km, and cloud optical depths from 8.0-200.0, summarized in Table 5.1.

To simulate satellite-retrieved radiance for the DSCOVR satellite, WRF-SBM-modeled cloud cases were fed into the Discrete Ordinates Radiative Transfer Model (DISORT) for solar zenith angles (SZA) from 0.0° through 72.0° and surface albedos (A_{sfc}) from 0.0 through 0.8. DISORT simulates the transfer of monochromatic and unpolarized radiation through a plane-parallel medium, calculating scattering, absorption, and emission (Stamnes and Dale 1981). It can use a variety of source radiation, such as Planck and diffuse sources, though the parallel beam is used here to simulate Earth-incident sunlight. Extinction calculated by DISORT includes aerosol effects, modeled by a distribution of calculated Legendre scattering coefficients; cloud effects, fed by COD calculated from the WRF-SBM data; and molecular effects, here assumed to be dominated by oxygen and driven by the convolved LBLRTM oxygen profile. The model result is a diverse database of cloud cases, on which the sensitivity
Finally, to analyze the sensitivity of this radiance dataset to various optical and geometric properties, a non-linear least squares fitting method was applied, using the curve_fit function from the Scientific Python module SciPy (Jones et al. 2001–). This fitting method differs from its linear counterpart by using an iterative approach to "best guesses" for the
individual fit parameters and requires an explicit definition of the Jacobian matrix, and convergence criteria must be specified as non-linear problems are usually not globally concave. While non-linear solutions are typically inherently biased, the self-referential nature of comparison in this study over a consistent dataset keeps the analysis from suffering overmuch. Analysis of this sensitivity study relies heavily on the standard error of the regression, or "S-value", as the primary means for quantitatively determining and relating "goodness-of-fit" of each non-linear fit function. The S value reports the average distance from the line of regression in units of the dependent variable, making it a strong choice for communicating findings that are intuitive and easily compared. Additionally, the S-value can establish a confidence interval over the data, with plus or minus twice the value enveloping approximately 95% of the original observations. While R-squared or adjusted R-squared values
Figure 5.4: Binned frequency distribution of cloud optical depths as a function of cloud thickness.

are typically used to report goodness-of-fit, findings from Spiess and Neumeyer (Spiess and Neumeyer 2010) show R-squared and adjusted R-squared values do not always increase with better models and tend to consistently higher values for both significantly good and significantly poor models. As the R-squared statistic is based on the assumption of a linear model, it was passed over in this study in lieu of accounting for appropriate caveats.

5.2 Forward Model

Because this function was developed in pathlength-space, each separate component describing a different interaction and section of the atmosphere, or part of the pathlength traveled, is additive and can be adjusted as such. Referring back to Equation 2.6, restated
Table 5.1: Summary of variables used to run DISORT cases. Modelled ranges are a result of the selection of liquid-only cases from WRF-SBM cloud output, with the upper limit on cloud optical depth of 200 established to be consistent with initial goals of capturing typical cloud behavior.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Range</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Modelled Cloud Parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cloud Optical Depth</td>
<td>8.0–200.0</td>
<td>31.4</td>
<td>21.1</td>
</tr>
<tr>
<td>Cloud Base Height (km)</td>
<td>0.1–6.5</td>
<td>1.2</td>
<td>0.7</td>
</tr>
<tr>
<td>Cloud Top Height (km)</td>
<td>0.9–7.5</td>
<td>3.4</td>
<td>1.5</td>
</tr>
<tr>
<td>Cloud Geometric Thickness (km)</td>
<td>0.3–7.4</td>
<td>2.2</td>
<td>1.5</td>
</tr>
<tr>
<td>Surface Albedo</td>
<td></td>
<td>0.0–0.8</td>
<td></td>
</tr>
<tr>
<td>Solar Zenith Angle</td>
<td></td>
<td>0.0–67.0</td>
<td></td>
</tr>
</tbody>
</table>

here, we now have a discrete function of mean pathlength in Equations 5.1 and 5.2. Figure 5.5 illustrates the atmospheric components of the forward model functions, emphasizing the discrete pathlength-simulating components. The first term in both equations describes the above-cloud effects. Employing the equivalence theorem, which describes total extinction as the sum of absorption and scattering, allows the determination of cloud top scattering by removing the oxygen absorption contribution. While the radiative transfer equation (RTE) scattering geometry can be simplified as in Equation 5.3, the simplification goes further by considering the near-equivalence of SZA and satellite view angle. Mu, described as the air mass ratio, is calculated by the inverse of the SZA, and, with the aforementioned equivalence, \( \mu \) and \( \mu_0 \) can be combined to result in the phrase in Equation 5.3. The azimuthal dependence, represented by \( \psi \), is decoupled from zenith dependence through the Fourier expansion of the RTE. Azimuthal dependence is significant only in single-scattering cases, and the ratio of
Figure 5.5: Illustration of photon path considerations for the non-linear forward model fitting and their equivalent $\tau_{O_2}$. Satellite visualization attributed to NASA-NOAA from NOAA Satellite and Information Service (2015)

single- to multiple-scattering cases for atmospheres with optical depths of the magnitude in this study are sufficiently small (Duan 2005). Subsequently, for EPIC geometry, azimuthal dependence is simply a constant. Leveraging the equivalence theorem, the assumption of identical SZA and view angle, and the decoupling of azimuthal dependence all continue to apply in the remainder of this function.
\[-\ln \left( \frac{R_A}{R_r} \right) = \frac{2}{\mu} \int_{CTH}^{TOA} \tau_{O_2} \]
\[+ a_1 \left( \int_{CTH}^{TOA} \tau_{O_2} \right)^{\beta_1} + b_1 \left( \int_{CTH}^{TOA} \tau_{O_2} \right) \left( a_2 T^{\beta_2} + b_2 \mu + c_2 \mu T + d_2 \mu^2 \right) \]
\[+ \left( \int_{CBH}^{CTH} \tau_{O_2} \right)^{\beta_3} \left( a_3 T^{\beta_2} + b_3 \mu + c_3 \mu T + d_3 \mu^2 \right) \]
\[+ \left( \int_{BOA}^{CBH} \tau_{O_2} \right)^{\beta_4} \left( a_4 T^{\beta_2} + b_4 \mu + c_4 \mu T + d_4 \mu^2 \right) \]
\[+ \frac{A_{sfc}}{1 + A_{sfc}(g + hT + kT^{\beta_5})} \]

\[-\ln \left( \frac{R_B}{R_r} \right) = \frac{2}{\mu} \int_{CTH}^{TOA} \tau_{O_2} \]
\[+ a_1 \left( \int_{CTH}^{TOA} \tau_{O_2} \right)^{\beta_1} + b_1 \left( \int_{CTH}^{TOA} \tau_{O_2} \right) \left( a_2 T^{\beta_2} + b_2 \mu + c_2 \mu T + d_2 \mu^2 \right) \]
\[+ \left( \int_{CBH}^{CTH} \tau_{O_2} \right)^{\beta_3} \left( a_3 T^{\beta_2} + b_3 \mu + c_3 \mu T + d_3 \mu^2 \right) \]
\[+ \left( \int_{BOA}^{CBH} \tau_{O_2} \right)^{\beta_4} \left( a_4 T^{\beta_2} + b_4 \mu + c_4 \mu T + d_4 \mu^2 \right) \]
\[+ \frac{kA_{sfc}}{1 + A_{sfc}(g + hT + kT^{\beta_5})} \]

\[f(\Delta \tau_{O_2}, \mu_0, \mu, \phi) = f(\Delta \tau_{O_2})g(\mu_0, \mu, \phi) \]
\[= \Delta \tau_{O_2} \left( \frac{1}{\mu} + \frac{1}{\mu_0} \right) \]
\[= \frac{2}{\mu_0} \tau_{O_2} \] (5.3)

Properly handling the photon penetration issue requires a cloud top interface and in-cloud phrase to be populated. The cloud top term accounts for both strong and weak
absorption tendencies with the linear and exponential terms scaling CTH (in $\tau_{O_2}$ form). An asymptotic approximation of plane-parallel reflectance, as described in Equation 5.4 and taken due to the asymptotic behavior of COD, gives a transmissivity term and trailing quadratic form. This quadratic term is applied to each of the cloud interface, in-cloud, and below cloud phrases as functions of air mass ratio and transmissivity. Transmissivity, $T$, is given in Equation 5.5 as a function of COD and the "asymmetry factor", or first cloud droplet phase moment, $g$, assumed here to be 0.85336. Stepping through this idealized atmospheric path, the cloud thickness phrase replaces the strong and weak cloud top term with a cloud thickness term, describing the distance between the top and bottom of the cloud in $\tau_{O_2}$ units. Similarly, the subsequent below-cloud phrase takes the thickness, in $\tau_{O_2}$ between the surface and the bottom of the cloud.

$$R(\tau, \mu, \mu_0, \phi) = R_\infty(\tau, \mu, \mu_0, \phi) - TK(\mu)K(\mu_0)$$

$$= R_\infty(\tau, f_1(\mu_0)) - Tf_2(\mu_0)$$

(5.4)

$$T = \frac{1}{0.75\tau_{cld}(1 - g) + 1.072}$$

(5.5)

Finally, the last phrase considered concerns itself with surface albedo, the general form of which is given in Equation 5.6. Such a shape is due to the dependence on spherical albedo $\bar{\sigma}$, the surface albedo when the incident radiation is considered isotropic. Since our radiation model considers a plane-parallel assumption with quasi-Lambertian reflecting surfaces, the isotropic component must be considered. We related this term to a dependence on transmissivity, itself a function of COD and cloud particle size and shape.

$$A$$

$$\frac{1}{1 + A\sigma(\tau_{cld}, r_e)}$$

(5.6)
In comparing the behavior of A- and B-band fitting models, it is important to highlight the relatively lower absorption for B-band with respect to A-band, as can be seen in Figure 4.2.

5.3 Results

Results of the sensitivity study show a dependence of satellite radiance retrieval on an interaction of variables rather than a straightforward linear combination of individual variables. Ultimately, the final A-band and B-band fitting functions, shown in equations 5.1 and 5.2, have an S-value of 0.0375 for A-band and 0.0227 for B-band. Many of the plots that follow show simulated retrievals versus their fit results in units of \(-\ln\left(\frac{R}{R_0}\right)\), referred to as log-ratio here; while it is an unintuitive value, it allows the computation of our pathlength-dependent function, as described in Section 2.2. To clarify the quality of radiation retrieved for a given log-ratio value, Figure 5.6 provides a brief schematic. Essentially, low log-ratio values describe cases of low oxygen absorption, and high log-ratio values describe cases of high oxygen absorption. Histograms of relative error for A-band and B-band forward models are shown in Figures 5.7 and 5.8. Overall, The forward model for A-band shows a remarkably good fit, with 95% of the data falling within plus-or-minus 5% error, and 75% of the data falling within 1\(\sigma\) % error. Peak error is slightly positive, implying a slight overestimation of retrieved-reflectance. B-band has a wider spread of error, though 91% of the data is within 5% error, and 74% of the data is within 1\(\sigma\) % error. Analysis of the efficacy of various fitting functions in this study benefitted from the partitioning of variables into subsets, typically higher values and lower values, to better identify areas of strong sensitivity within and across fit functions. These subsets have individually calculated S-values and error distributions to describe their contribution to the overall fit, but were not individually processed in the non-linear fitting algorithm.
5.3.1 Surface Albedo

Surface albedo, a measure of the reflectance of the underlying surface, in this study ranges from 0.0, an entirely "black", non-reflective surface, to 0.8, a typical value for snow cover. It is important to note that, while the low and high cases are of the same size, the black case is half that size. Analysis of only the 0.0 albedo case in the A-band regime gives an S-value of 0.034 and gives a strong fit for the data, as can be seen in Figure 5.10. Excluding high albedo cases, those above 0.4, increases the S-value from the zero case to 0.036, while only considering those high albedo cases markedly increases the S-value to 0.0401. These higher albedo cases show the most error, particularly in lower log-ratio cases. As lower log-ratio implies lower absorption, this behavior describes a stronger signal incident on a
highly reflective surface. Atmospheric paths of radiation can be complex and reducing signal absorption increases the likelihood of additional scattering processes. Results in the B-band show similar behavior in Figures 5.12, with S-values summarized in Table 5.3. Both A-band and B-band black subsets show a slant towards negative error values with a pronounced tail in the positive error direction, implying a slight underestimation of top-of-atmosphere (TOA) radiance (5.9, 5.11). This same shape is mimicked in both A- and B-band low $A_{sfc}$ cases, but with the peak of the A-band data occurring near 2% and the B-band data peak occurring near -2%. Additionally, while low $A_{sfc}$ values have a tight spread for the A-band simulation, the B-band simulation has a wider spread overall across all subsets. High $A_{sfc}$ shows a departure between A-band and B-band simulations, with a positive slant, though still slightly negative peak, for A-band and a more normal spread centered roughly around 0% for B-band. That
5.3.2 Solar Zenith Angle

Lower solar zenith angle (SZA) values, those representing TOA incidence close to nadir, almost completely encompass the lowest log-ratio values of this dataset for both A- and B-band. As lower log-ratio values are analogous to low absorption cases, this behavior can be explained by considering how much less of the atmosphere the signal must travel through between TOA incidence and satellite retrieval. The S-value for these lower values is 0.045 in the A-band while for the higher SZA values, those higher than 36° from nadir shown...
in Figures 5.14, the S-value is 0.0.034. The S-value does not change significantly in the B-band regime, the distribution of which is seen in Figure 5.16. Error spread illustrated by the subset histograms (5.13,5.15) further supports increased model error for lower solar zenith angles, though more so for the A-band regime than the B-band. The partitioning was kept consistent through both regimes in order to describe sensitivity for oxygen absorption across both band spectrums, though the scatter and error spread in the B-band simulation imply the need for a higher threshold to describe the error contributions of lower solar zenith angles.

5.3.3 Cloud Optical Depth

Breaking down cloud optical depth values into low and high categories, with values less than and greater than 25, respectively, reveals a strong dependence on COD for proper fitting. Higher values, implying optically thicker clouds, have an A-band fit S-value of 0.0.025, and a B-band fit of 0.020, and show strong visual fitting behavior, as can be seen in Figures 5.18 and 5.20. Lower COD values are a much poorer fit, encompassing the majority of the spread of the data and determining an S-value of 0.047 in the A-band and 0.026 in the B-band regime. Additionally, these values, particularly in low log-ratio cases, are decidedly underestimated than their simulated values, seen in Figures 5.18 and 5.20. Some rationale for this behavior can be determined by considering the effect of near-nadir top-of-the-atmosphere (TOA) incidence of solar radiation; a more direct path through the atmosphere and less scattering from clouds with lower COD implies less time overall spent in the atmosphere. The fit seems to overestimate the amount of attenuation of the signal before exiting the atmosphere and reaching the satellite. Behavior in the relative error histograms (5.17) of cloud optical depth impacts on retrieval error is particularly interesting for the A-band model, as there exist two local maxima on either side of 0% error for the low-COD case. This, combined with a much wider spread of error, implies a less-than-ideal capture of cloud optical depths less than 25. Similarly, lower COD cases are responsible for the highest
magnitude of error in the B-band model \((5.19)\), with the dataset’s overall trend towards overestimation of TOA reflectance occurring in both low and high cases. Higher CODs in the A-band case have a quasi-normal distribution centered near 0\% with a narrow spread, emphasizing the improved capture of higher cloud optical thickness behavior.

5.3.4 Cloud Top/Bottom Height

Cloud top height (CTH), as well as cloud bottom height (CBH), measurements are reported here in units of "integrated oxygen optical depth", referred to as \(\tau_{O_2}\) throughout this assessment; note the dropped integral symbol for brevity. This is a measure of integrated oxygen optical depth from the TOA to the top of the cloud established in Section 2.2 as the optimal vertical unit. These variable subsets have different thresholds as oxygen absorption in the B-band regime is smaller and, as such, have different values at similar layers. Cloud bottom height behavior is difficult to capture in this method; variable subset partitions were chosen to emphasize behavior in the overall data spread while not prioritizing the amount of data captured. Thus, the low \(\tau_{O_2}\) case, which implies higher geometric heights, has significantly less data than its high \(\tau_{O_2}\) counterpart. However, some information can be gleaned from comparing the spread of the two, particularly in the B-band case \((5.25, 5.27)\). Lower CBH \(\tau_{O_2}\) cases are shown to be over-estimated by the B-band forward model, while higher cases are slightly underestimated, by nearly the same factor. However, there is no significant difference, other than magnitude, of the curve of the A-band cloud bottom height subsets. Similarly, cloud top height partitioning reveals little additional data besides emphasizing the contribution to higher error values for low \(\tau_{O_2}\) cloud tops (higher geometric cloud tops) in both A- and B-band. \((5.21, 5.23)\) Higher CTHs do help characterize the spreading of the data in the low log-ratio values, providing cases which minimize the amount atmosphere and, subsequently, oxygen the radiation must travel through before cloud incidence and scattering. These cases have an S-value of 0.033 and are shown in Figure 5.22. Lower CTHs, represented by higher \(\tau_{O_2}\) in Figure 5.22, are somewhat tighter and have an improvement in fit with a
subsequent $S$-value of 0.033. As is the case with previous variable assessment, CTH does not solely control the trend here; greater fit improvements were found when considering COD and CBH partitions.

5.3.5 Geometric Cloud Thickness

Even with increased complexity in the fitting function, geometrically thinner clouds fit the poorest and had behavior that was the hardest to capture. Clouds that were less than 1.0km thick gave an $S$-value of 0.037 and 0.026 for A- and B-bands, respectively, and included most of the cases with the greatest spreading. Thin clouds are often more sensitive to effects from the interdependence of multiple variables, such as increased surface albedo with lowered COD. More importantly, radiance retrievals involving geometrically thin clouds will be significantly more dependent on absorptive effects than cloud scattering. Moderately thick clouds, ranging from 1.0-2.5km, had an $S$-value of 0.036 for A-band and 0.022 for B-band and encompassed a moderate amount of the poorly fit data in Figure 5.30, though this can be attributed to the larger number of cases in this regime. Highly thick clouds, from 2.5km and upwards, had an $S$-value of 0.040 for the A-band model, and its tighter spread can be seen in Figure 5.30. While the expectation is such that model error should decrease with increasing geometric thickness of clouds, as through-cloud photon penetration and surface effects are reduced, the shape and spread of the three subsets do not show such a trend in either the A- or B-band regime (5.29, 5.31). Two of the most likely reasons for this lack of error dependence are either A) the retrievals themselves are insensitive to cloud geometric thickness, or B) the forward model captures the sensitivity of TOA-reflectance to cloud thickness. As Yang et al. (2013) and others have clearly shown, there is a strong dependence on geometric thickness, so this behavior likely supports goodness-of-fit for the forward model.
5.3.6 Discussion

Much of the variance in this fitting method has been shown to come from cases of high, thin clouds with low COD, in situations of low SZA and high $A_{sfc}$. Table 5.2 summarizes these and the remainder of the distribution of subset S-values. While retrievals are strongly sensitive to COD and CBH, particularly higher CBHs, view geometry had a nearly equivalent impact as well. As discussed previously, this can be attributed to the limiting of absorption along the path due to the shorter path traveled. Increasing COD increases the relevance of the Lambertian surface assumption of the cloud top surface and decreases the adjustment necessary for photon penetration, the specifics of which are discussed in the following section. Higher cloud bottom heights more effectively constrain cloud top height and, subsequently, cloud thickness, so are the best indicator of retrieval sensitivity to both height and thinness. B-band absorption is much weaker, making retrievals in this narrowband spectrum far more susceptible to below-cloud and surface effects. While the overall S-value fit for B-band is similar to that of A-band, the much lower log-ratio values it describes indicates an overall poorer fit. The variable partition values for B-band are summarized in Table 5.3. B-band fitting expresses similar behavior to that of A-band in that retrieval sensitivity is highest with high, thin clouds with low COD, high $A_{sfc}$, and low SZAs.
Figure 5.9: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for ${A_{\text{sfc}}}$ cases, and distribution of relative error for each subset. Black ${A_{\text{sfc}}} = 0.0$, Low ${A_{\text{sfc}}} = 0.2 – 0.4$, and High ${A_{\text{sfc}}} = 0.6 – 0.8$

Figure 5.10: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each ${A_{\text{sfc}}}$ subset case.
Figure 5.11: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for $A_{sfc}$ cases, and distribution of relative error for each subset. Black $A_{sfc} = 0.0$, Low $A_{sfc} = 0.2 – 0.4$, and High $A_{sfc} = 0.6 – 0.8$

Figure 5.12: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each $A_{sfc}$ subset case.
Figure 5.13: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for SZA cases, and distribution of relative error for each subset. Low SZA = 0.0 – 36.0, and High SZA = 36.0 – 66.0

Figure 5.14: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each SZA subset case.
Figure 5.15: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for SZA cases, and distribution of relative error for each subset. Low SZA = 0.0 – 36.0, and High SZA = 36.0 – 66.0

Figure 5.16: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each SZA subset case.
Figure 5.17: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for COD cases, and distribution of relative error for each subset. Low COD = 0 – 25, and High COD = 25 – 200

Figure 5.18: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each COD subset case.
Figure 5.19: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for COD cases, and distribution of relative error for each subset. Low COD = 0 – 25, and High COD = 25 – 200

Figure 5.20: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each COD subset case.
Figure 5.21: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for $\tau_{\text{O}_2}$CTH cases, and distribution of relative error for each subset. Low $\tau_{\text{O}_2}$CTH = 0 – 0.45, and High $\tau_{\text{O}_2}$CTH = 0.45 – 0.62

Figure 5.22: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each $\tau_{\text{O}_2}$CTH subset case.
Figure 5.23: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for $\tau_{O_2}\text{CTH}$ cases, and distribution of relative error for each subset. Low $\tau_{O_2}\text{CTH} = 0 - 0.20$, and High $\tau_{O_2}\text{CTH} = 0.2 - 0.3$

Figure 5.24: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each $\tau_{O_2}\text{CTH}$ subset case.
Figure 5.25: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for $\tau_{O_2}$CBH cases, and distribution of relative error for each subset. Low $\tau_{O_2}$CBH = 0 – 0.45, and High $\tau_{O_2}$CBH = 0.45 – 0.62.

Figure 5.26: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each $\tau_{O_2}$CBH subset case.
Figure 5.27: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for $\tau_{O_2}$CBH cases, and distribution of relative error for each subset. Low $\tau_{O_2}$CBH = 0 – 0.20, and High $\tau_{O_2}$CBH = 0.2 – 0.3

Figure 5.28: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each $\tau_{O_2}$CBH subset case.
Figure 5.29: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for GTHK cases, and distribution of relative error for each subset. Low GTHK = 0.0 – 1.0, Mid GTHK = 1.0 – 2.5, and High GTHK = 2.5 – 7.4

Figure 5.30: Visualization of A-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each GTHK subset case.
Figure 5.31: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit colored for GTHK cases, and distribution of relative error for each subset. Low GTHK = 0.0 – 1.0, Mid GTHK = 1.0 – 2.5, and High GTHK = 2.5 – 7.4

Figure 5.32: Visualization of B-Band Forward Model comparison between simulated EPIC pixels and modeled fit for each GTHK subset case.
<table>
<thead>
<tr>
<th>Variables</th>
<th>S-Value</th>
<th>ΔS</th>
<th>% Change</th>
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<td>0.004</td>
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<td>0.008</td>
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<tr>
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<tr>
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<td>0.003</td>
<td>8.11</td>
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Table 5.2: S-value distribution for A-band variable subset analysis. Departures beyond 15% of the whole-dataset S-value are highlighted in bold.
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<th>% Change</th>
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<tr>
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<tr>
<td>High</td>
<td>0.022</td>
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Table 5.3: S-value distribution for B-band variable subset analysis. Departures beyond 10% of the whole-dataset S-value are highlighted in bold.
6. Conclusion

This was a study of the sensitivity of satellite radiance retrieval to various cloud geometric and optical properties, as well as varied atmospheric properties and view geometries. An atmospheric profile consisting of satellite filter function-convolved oxygen optical depth was created for use as background absorption and atmospheric-unspecific vertical coordinate. A database of liquid cloud cases was populated and refined from cloud data modeled in WRF-SBM, and then was used as input for the DISORT model to simulate satellite-retrieved radiances. A sensitivity study of such radiances was performed for both oxygen A- and B-band absorption regimes, and a non-linear fitting function capturing such sensitivity was defined. This fitting function results in a description of satellite-retrieved radiance in a strong absorption and nearby weak absorption band as a function of cloud characteristics and view geometry and characteristics.

As the goal of this fitting method was to capture behavior of cloud parameters over the entire sun-lit hemisphere, a major concern that the cloud cases dataset is broad enough to apply. The WRF-SBM study was chosen not only for its natural evolution of cloud microphysics, but its high temporal and spatial resolution. Such detailed data of stratiform and convective clouds was considered to be sufficient to capture the majority of global liquid cloud behavior. Additionally, with 19,170 model observations of clouds, expanded in DISORT over the spectrum of surface albedos and solar zenith angles, results in a total of 1,437,750 fitting model observations. While there are certainly a large number of fitting parameters for this complex dataset, there are sufficient observations to dispel considerations of overfitting for this model. Additionally, this fitting function should not have to be expanded much farther outside the tested bounds since, as was previously discussed, the dataset was designed to be largely exhaustive in its encompassing of cloud cases.
\[ \rho_W(h, T) = \begin{cases} 
  w_0 \left( \frac{h-h_b}{h_r} \right)^a \cdot (1 + cT), & T \geq 0^\circ C \\
  w_0 \left( \frac{h-h_b}{h_r} \right)^a \cdot \exp(cT), & T < 0^\circ C 
\end{cases} \tag{6.1} \]

\[ \rho_L = \rho_W(h, T) \cdot f_W(T) \tag{6.2} \]

\[ \rho_{ICE} = \rho_W(h, T) \cdot (1 - f_W(T)) \]

Finally, the homogenous vertical distribution of liquid water content LWC through the cloud must be considered. A number of attempts at prescribing a realistic LWC profile for each case were considered but this method requires some a-priori specification of the clouds in question and, as such, is unrealistic within this instrument observation at an operational level. Of most potential is the Salonen model [Salonen and S., 1991], from which other studies have evolved (Mattioli et al., 2006; 2009). This method requires a reference liquid water content based on cloud reference height and subsequent temperature (see Equations 6.1 and 6.2, too strong of a limitation for this model considering such wide atmospheric variation needing consideration. Other models, such as the Decker model (Mattioli et al., 2006) require comparison with co-located radiosonde or other moisture-measuring instrumentation, an inviable system for global measurements. However, satellite water vapor and other water content measurements are available, and this method of solving for LWC profiles in EPIC retrievals could be useful when used in tandem with such a sensor. Non-DSCOVR instrumentation combination could significantly reduce operational speed, but such a product could be best used as a corrected or reanalysis dataset.

Overall, this study provides a fitting method to adequately capture satellite radiance retrievals as a function of cloud and atmospheric properties and view geometry, ultimately leading to a look-up-table for satellite-retrieved cloud top height for the EPIC sensor on board the DSCOVR satellite. This was accomplished through the leveraging of oxygen
A- and B-band absorption, mean photon pathlength, and convenient satellite-Earth-Sun geometry.
BIBLIOGRAPHY


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