Towards an optimal estimation retrieval of cirrus cloud optical and microphysical properties using hyperspectral shortwave instruments and a fast radiative transfer algorithm

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INTRODUCTION

- Cirrus clouds are important modulators of atmospheric radiation.
- Accurate satellite ice cloud retrievals are needed for global observational products.
  - However, ice cloud products have large uncertainties.
- One approach to reducing retrieval uncertainties is to increase the number of instrument channels.
- We are developing a pair of cirrus cloud retrievals for hyperspectral reflective solar instruments:
  - A high-speed retrieval using PCRTM-Solar.
  - A physically rigorous, and computationally slower retrieval.
- This poster presents preliminary uncertainty results from the development of a physically rigorous, computationally slower, retrieval.
- Motivation for a computationally slower retrieval:
  - Verify results from our in development high speed retrieval.
  - Study behavior of retrieval product uncertainties.

METHODS

- Both retrievals are being designed for Earth Surface Mineral Dust Source Investigation (EMIT) reflectances and will also target future Climate Absolute Radiance and Refractivity Observatory Pathfinder (CLARREO-PF) measurements.
- The physically rigorous method will use the optimal estimation (OE) retrieval framework [1].
  - The radiative transfer modeling (RTM) component of the forward model is a two-step approach:
    - Line-by-Line Radiative Transfer Model for atmospheric gas optical depth estimations.
    - Discrete Ordinates Radiative Transfer Model for radiative transfer with scattering.
- The example in this poster uses a standard midlatitude summer atmosphere.
- Cirrus clouds modeled as single layered over ocean water.
- Assume a gamma distribution $n(D) = N_0 \left(\frac{D}{\beta}\right)^{a-1} e^{-(D/\beta)}$ with α and β from [2].
- Assuming Two-Habit model for the primary ice cloud scattering database [3].
  - Additional bulk scattering properties from CERES Edition 4 and generated from TAMUice2016 used to estimate "habit uncertainty." See Fig. 1.

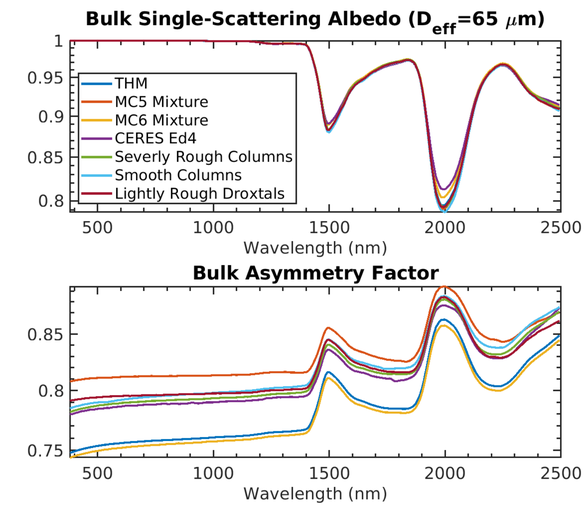


Fig. 1. Example of seven bulk scattering properties for ice clouds with D_{eff} = 65 μm. Upper plot is bulk single-scattering albedo $(\tilde{\omega})$. The lower plot is bulk asymmetry factor (g).

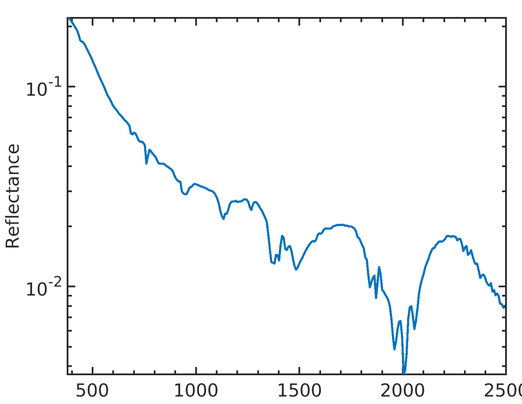


Fig. 2. Example synthetic EMIT reflectance spectrum for modeled cirrus cloud used in estimating uncertainties below.
z_{top}=~12 km
$\tau_{cld} = 1.0$
$D_{eff} = 65\ \mu m$

UNCERTAINTY ANALYSIS

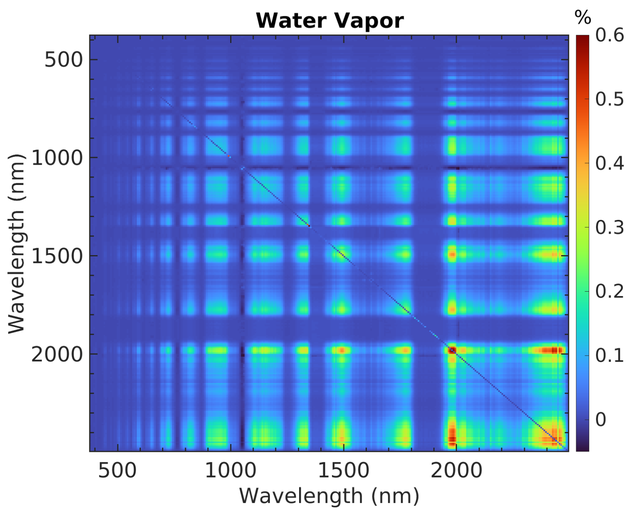


Fig. 3. Reflectance uncertainty matrix due to uncertainty in water vapor volume mixing ratio. Diagonal estimated by propagating published MERRA-2 relative humidity and temperature relative uncertainties to water vapor volume mixing ratio uncertainty, then to reflectance uncertainty. Off-diagonal covariances estimated by first assuming estimated water vapor volume mixing ratio uncertainties are Gaussian, randomly generating 100 atmosphere profiles, calculating reflectances from the RTMs, then calculating channel covariances. The matrix is displayed as the percentage of the error divided by the product of channel reflectances (see equation (1))

- Important components in OE are the error covariance matrices representing model and measurement uncertainties.
- We show an example case for a cirrus cloud in a midlatitude summer atmosphere, z_{top}=~12 $km, \tau_{cld} = 1.0, D_{eff} = 65\ \mu m$.
- Three error covariance matrices are considered:
  - S_{WV} represents reflectance uncertainty from water vapor volume mixing ratio uncertainty. See Fig. 3.
    - Propagated from published MERRA-2 relative humidity and temperature uncertainties to RTM [4]
  - S_{habit} represents reflectance uncertainty due to selection of an ice particle scattering model. See Fig. 4.
    - Channel reflectance variance/covariance calculated using bulk scattering models shown in Fig. 1.
  - S_{inst} = Reflectance uncertainty due to the instrument.
    - Assuming an instrument uncertainty of 5%.
  - $S_\varepsilon = S_{WV} + S_{habit} + S_{inst}$ represents the combined uncertainty. See Fig. 5.
- For ease of interpretation Figs. 3-5 show relative uncertainties [5]:
  - $C(i,j)\% = 100 \times \begin{cases} \sqrt{\frac{S_x(i,j)}{R_i R_j}}, S_x(i,j) > 0 \\ -\sqrt{\frac{-S_x(i,j)}{R_i R_j}}, S_x(i,j) < 0 \end{cases}$ (1)
    - $S_x(i,j)$ is the covariance between channels *i* and *j*
    - $R_i R_j$ is the product of channel reflectances

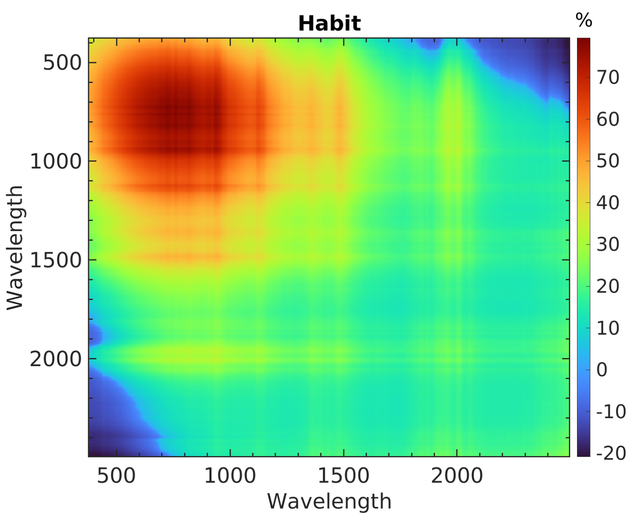


Fig. 4. Reflectance uncertainty due to the selected scattering model. Each pixel in the image is the covariance between channel reflectances for seven bulk scattering models. See Fig. 1 for the seven bulk scattering models.

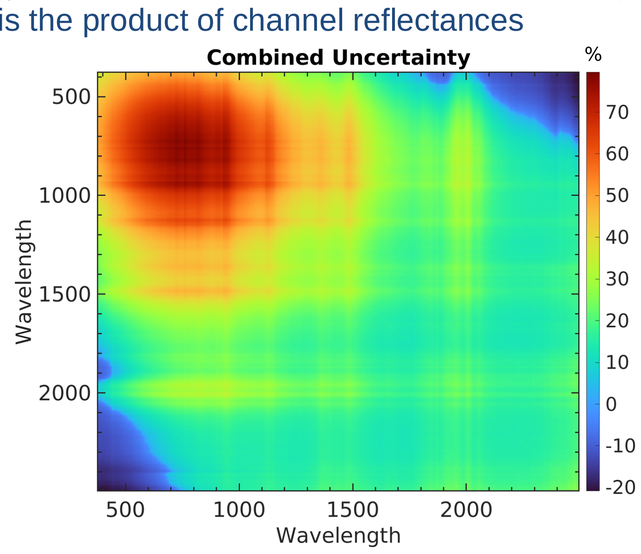


Fig. 5. The combined reflectance uncertainty. The covariance matrix is estimated by:$S_\varepsilon = S_{WV} + S_{habit} + S_{int.}$. The matrix is represented as a percentage. This and Fig. 4 show that Habit uncertainty dominates over water vapor mixing ratio and Instrument uncertainties.

SUMMARY/DISCUSSION

- We are developing a physically rigorous cirrus cloud OE retrieval for reflective solar hyperspectral instruments to verify a future high-speed retrieval.
  - Here we present an uncertainty analysis.
  - Reflectance uncertainties due to water vapor uncertainty are a max 0.6%, mostly $< 0.4\%$ in the presented example.
  - Habit uncertainty dominates all others.
- This work is a follow-on to [6]:
  - There the authors found - using all channels in a hyperspectral instrument maximizes the cumulative Shannon information content (SIC, a figure of merit for uncertainty reduction) over multispectral instruments in the same spectral region.
- We can assume a series of notional instrument uncertainties and the SIC can be estimated for comparisons of possible hyperspectral instruments.

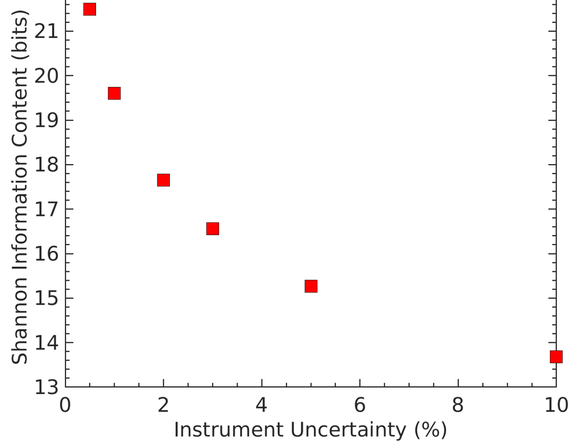


Fig. 6. This shows the effect of increasing/decreasing instrument uncertainty on SIC. SIC is an intermediate product of OE.

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