Harnessing AOS Observations for Advanced Understanding of Cloud Radiative Fluxes

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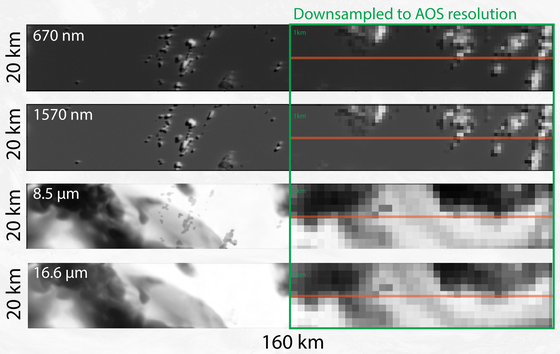
Introduction:

Understanding the complexities of cloud-sky radiative fluxes is crucial for improving numerical predictions of climate change. NASA's upcoming Atmosphere Observing System (AOS) mission promises unprecedented observations that will present an opportunity to enhance our understanding of the role of clouds in modulating both Earth's radiation budget and climate sensitivity.

AOS will utilize a series of active (Radar, Lidar) and passive (Imaging multi-angle polarimeter) instruments. The active instruments will provide vertically resolved cloud and aerosol information over a narrow ground-track (shown in red in the Figure below), while the passive instruments will cover a much wider swath. The high spatial resolution of AOS (~1km) will allow us to study clouds at the process level. While this will give us the opportunity to gain new insights, it also provides an unprecedented challenge to deliver satellite products at such a high resolution at which horizontal photon transport cannot be neglected, leading to biases in traditional cloud retrieval algorithms.

To estimate radiative fluxes over the whole swath, we propose to extrapolate the vertical information from the active instruments to the across-track passive observations using a scene construction algorithm. This algorithm is evaluated using data from Large-Eddy Simulations and synthetic imagery computed by radiative transfer models (see Figure below).



Simulated radiances from a Large-Eddy Simulation (LES) at 670 nm, 1570 nm, 8.5 µm, and 16.6 µm. The left part of the scene is shown in the native resolution of the simulation. The right part of the scene has been coarsened to the AOS resolution of 1 and 2 km. The red line shows the ground-track where AOS will provide vertically resolved measurements.

Objective:

Construct 3D scenes from passive and active AOS sensors. Use vertical cloud profile information from radar + lidar available for a narrow ground-track and "extrapolate" information to across track pixels using the passive wide swath radiance measurements.

Generating the AOS observations:

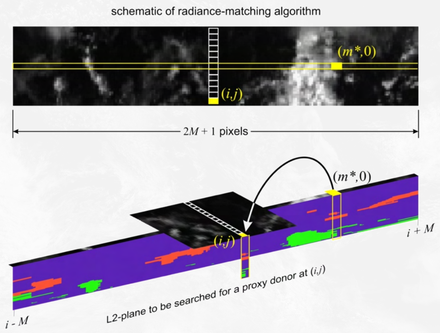
Simulated AOS observations with 20 LES scenes that were generated in preparation for the INCUS and EarthCare mission and a RICO case study. Scenes varie in size from 80 km x 80 km to 50 km x 400 km.
Radiances were calculated using a 3D Radiative Transfer model (MCARATS/E3RT) for 550 nm, 670 nm, 865 nm, 940 nm, 1380 nm, 1570 nm and 1D modl (libRadtran) for 8.5 µm, 11.3 µm, 16.6 µm, 21.5 µm. The surface albedo was varied between 0.1 and 0.4, solar zenith angle between 10° and 60°, and solar azimuth angle between 0° and 360°.

Scene construction using Machine Learning:

We evaluate various interpretable machine learning based approaches:

- Nearest neighbor interpolation based on EarthCARE's scene construction algorithm [1] (see Figure below). Building on this approach we experiment with various methodsto make it more robust (K-Nearest Neighbors interpolation, Dimensionality Reduction with PCA) and more flexible (Non-Linear Nearest Neighbor interpolation, feature engineering with spatial patterns, consider physical proximity).
- More advanced but still interpretable regression based algorithms that allow to quantify uncertainties: Random Forest Quantile Regression and Gaussian Process Regression.

All models are applied in a local sense (train over a fixed window size, e.g. ±30 km in along track dimension and then predict across track pixels in center of window).



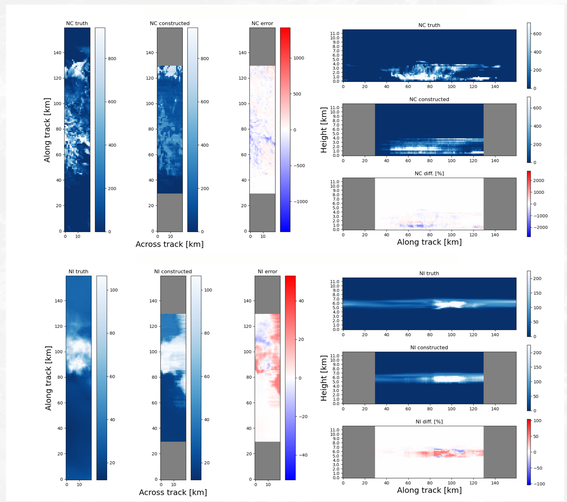
Scene Construction algorithm employed by EarthCare based on Nearest Neigbor interpolation. Column information is 'copied' to across-track pixels based on similarity in radiance space [1].

[1]: Qu, Z., Barker, H. W., Cole, J. N. S., & Shephard, M. W. (2023). Across-track extension of retrieved cloud and aerosol properties for the EarthCARE mission: the ACMB-3D product. Atmos. Meas. Tech., 16(9), 2319-2331. doi:10.5194/amt-16-2319-2023

Results:

For the local modelling approach we find the Random Forest to work best, closely followed by K-Nearest Neighbors, and Nearest Neighbor interpoloation. The following table shows the regression coefficients (R^2) for various vertically resolved cloud microphysical properties on the test set. The figure below shows the true, reconstructed, and error for integrated columns (left) and layers (right) for Cloud Droplet Number Concentration (NC) (top) and Ice Cystal Number Concentration (NI) (bottom).

	NC Cloud droplet # concentration	NI Ice crystal # concentration	QC Cloud water mixing ratio	QI Ice water mixing ratio	QV Water vapor mixing ratio
NEAREST NEIGHBOR	0.30	0.78	0.21	0.79	0.99
K-NEAREST NEIGHBOR	0.44	0.8	0.36	0.81	0.99
RANDOM FOREST	0.51	0.80	0.43	0.81	0.99



Future Work:

- Test if combining a global model (train and predict on all available LES scenes without a window) with the local model leads to better results. Combination could be based on estimated uncertainties of each model. That might help to better represent extreme values in reconstruction.
- Explore the use of features that use spatial information.
- Add more realism to AOS simulations: surface BRDF, varying surface types, aerosols
- Gain physical insight with explainable AI methods. Understand which features contribute to the prediction of physical properties. How does this change for different cloud structures.
- Gain better insight when scene construction fails, what are the impacts, what are possible ways to flag these instances.
- Translate scene construction errors into Radiance, Fluxes, and Heating Rate errors.