Relationships between cloud morphology and cloud microphysics derived from satellite remote sensing are biased by neglect of 3D radiative transfer

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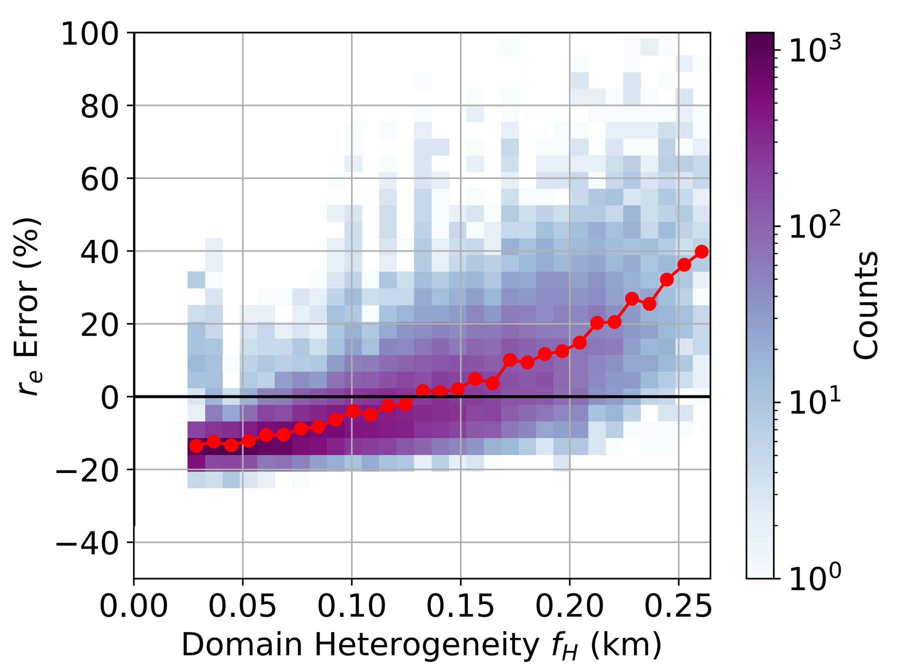
Summary

- A machine learning retrieval of droplet effective radius (r_e) is trained using 3D radiative transfer simulations and applied to Aqua-MODIS data over the ocean with the MEASURES low-cloud mesoscale morphology classifier (Yuan et al., 2020). CloudSat-CPR is used to identify precipitation.
- Biases in MODIS bispectral retrievals of r_e vary with cloud fraction and mesoscale morphology reaching up +70%.
- The covariance between droplet number concentration (N_d) and cloud fraction is revealed to be small.
- The covariance between N_d and precipitation frequency at the mesoscale is revealed to be strong.

Background

- Operational remote sensing retrievals of cloud optical depth and droplet effective radius assume that clouds form homogeneous, horizontally infinite slabs.
- This assumption causes systematic errors in remote sensing retrievals that vary with the heterogeneity of the cloud field and solar-viewing geometry and range from -15% to +40% even after subsampling following Grosvenor et al., (2018).



Acknowledgements

We gratefully acknowledge funding from NASA through the FINESST (80NSSC20K1633), ACCDAM (80NSSC21K1449) and remote sensing theory (80NSSC20K1719) programs. We thank all of the members of the CAMP²Ex team for their hard work collecting data, and the MODIS, CloudSat and CALIPSO teams for distributing their data products.

References

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Grosvenor et al. (2018). https://doi.org/10.1029/2017RG000593

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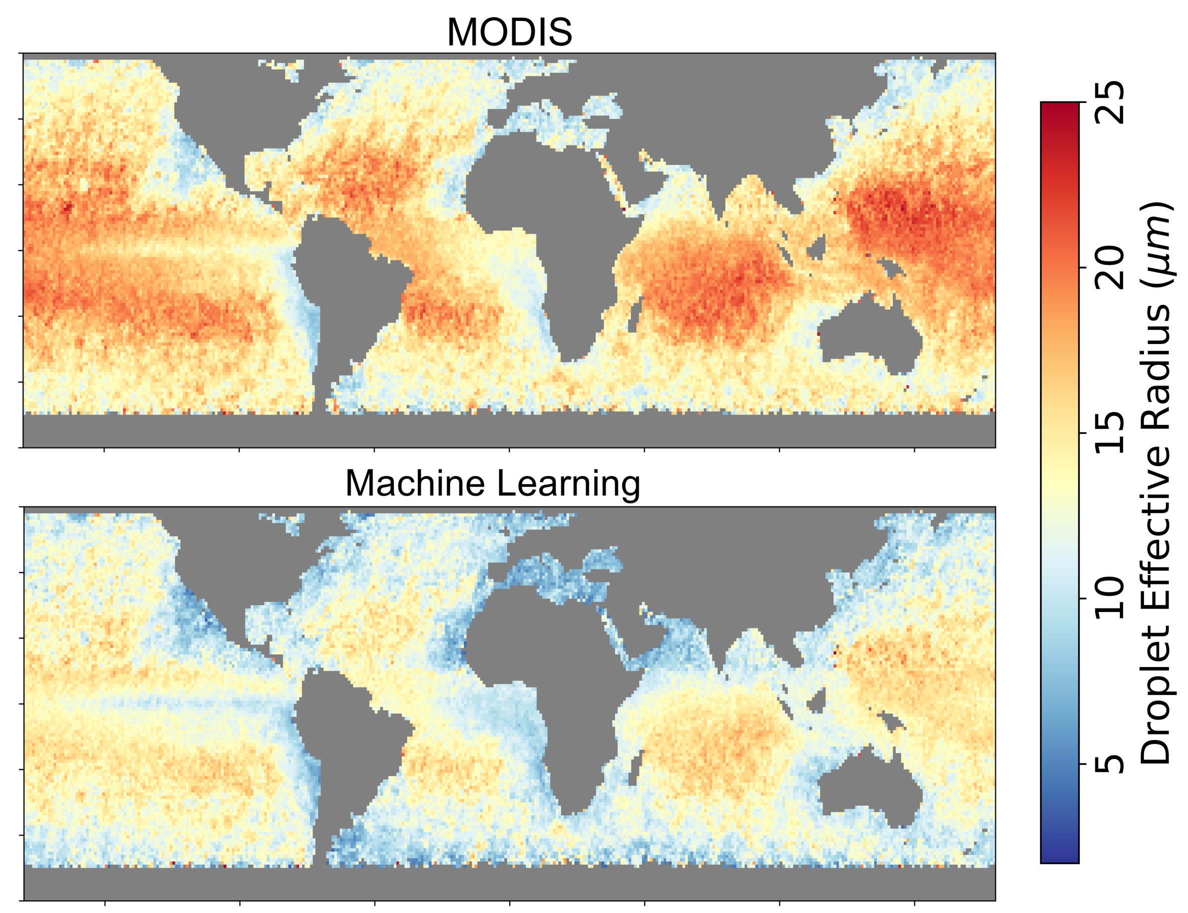
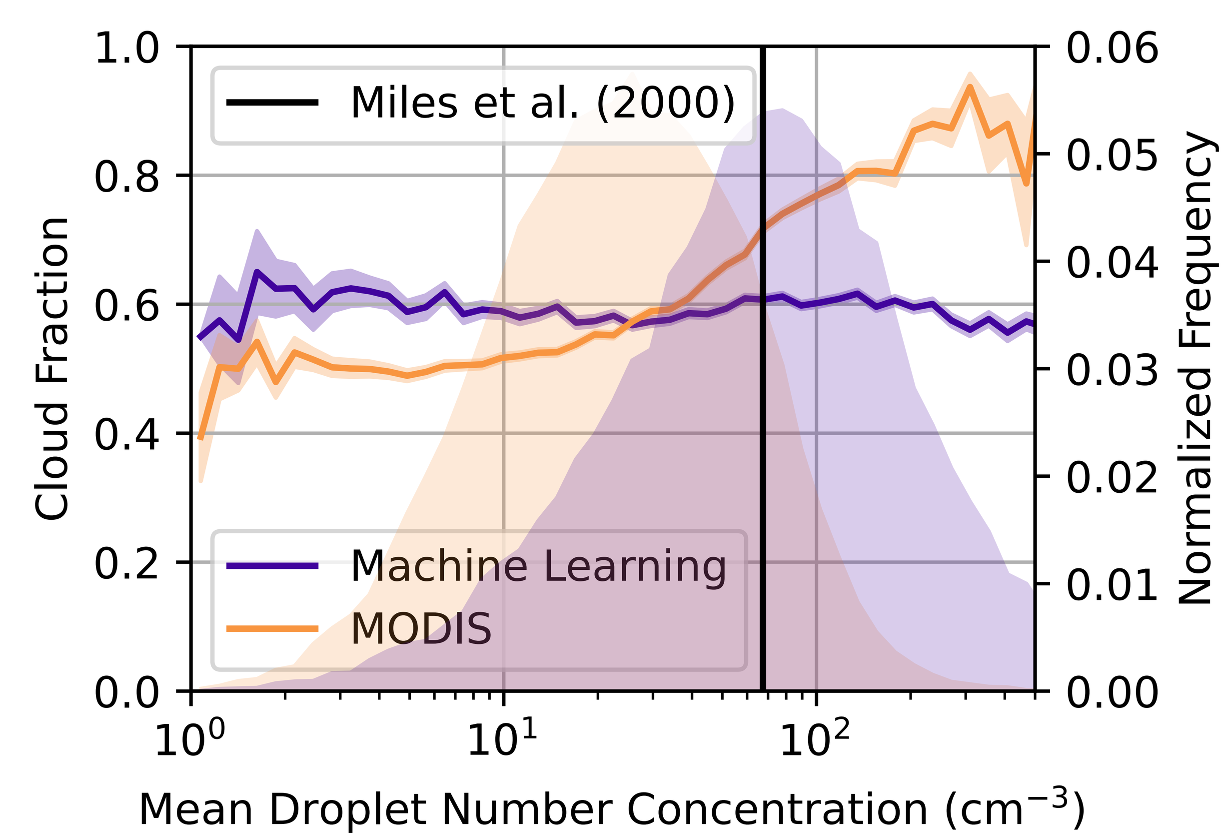
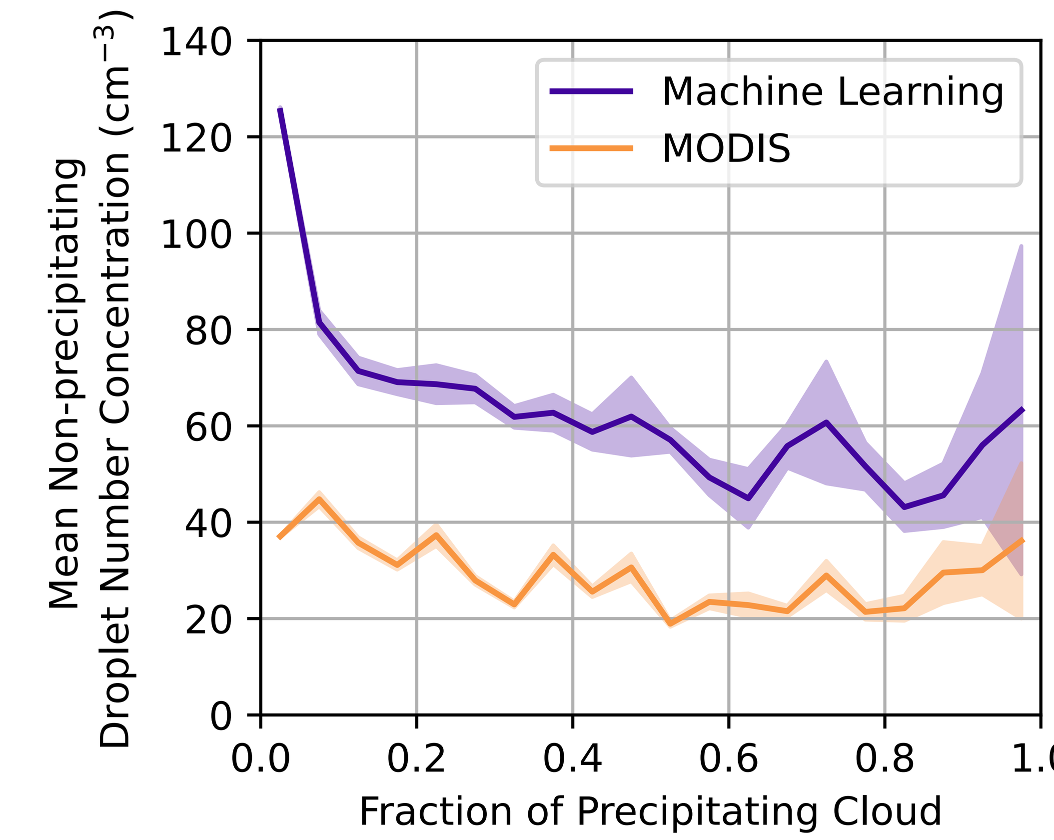
Climatology of Droplet Effective Radius



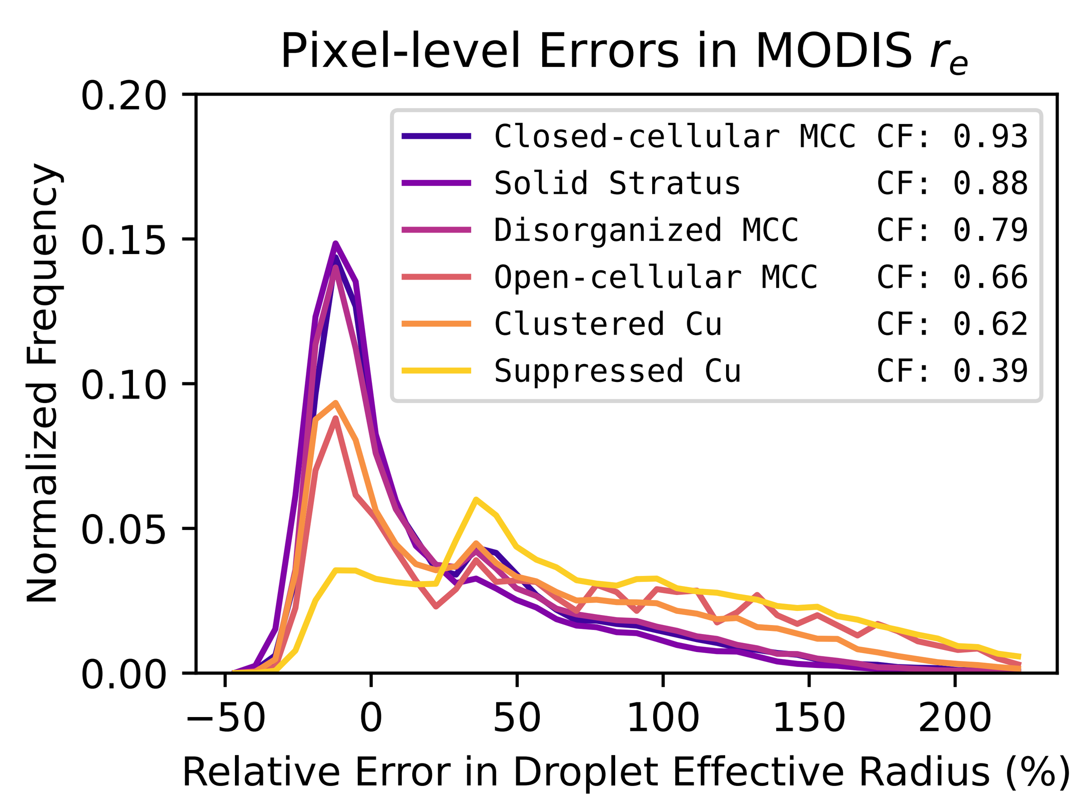
Covariance of N_d and Cloud Fraction



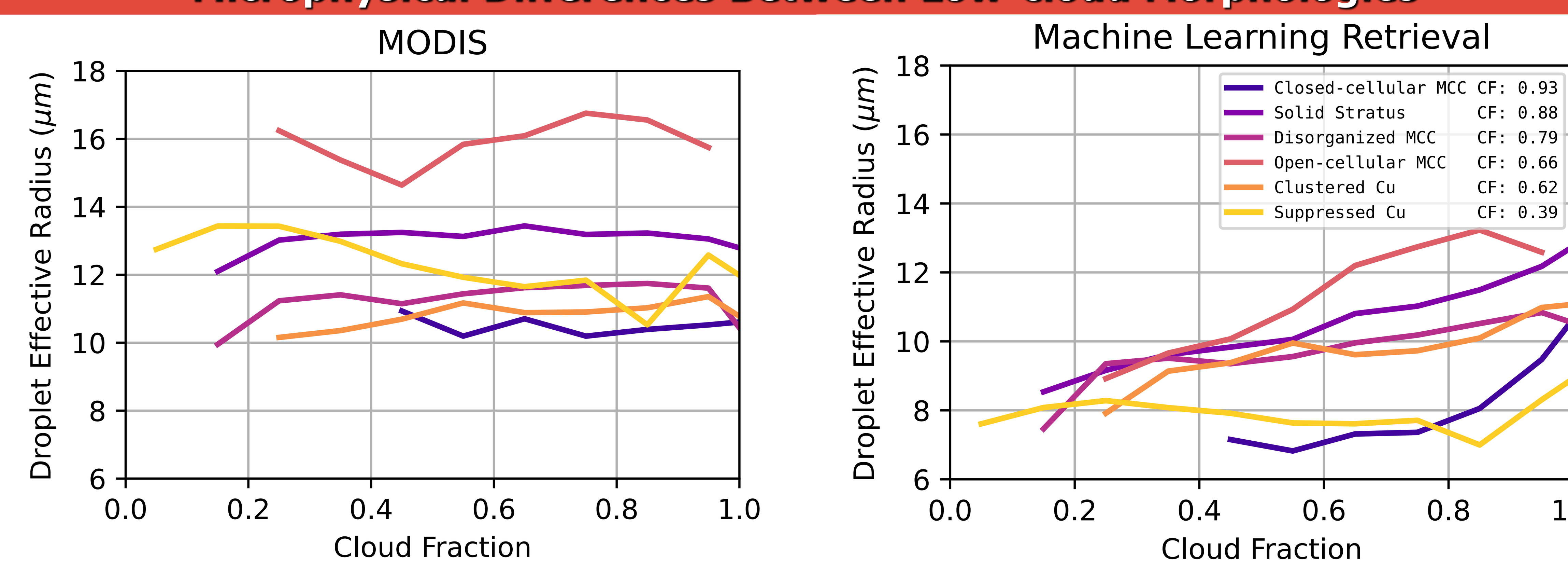
N_d and Precipitation Frequency



Retrieval Errors are Bimodal



Microphysical Differences Between Low-cloud Morphologies

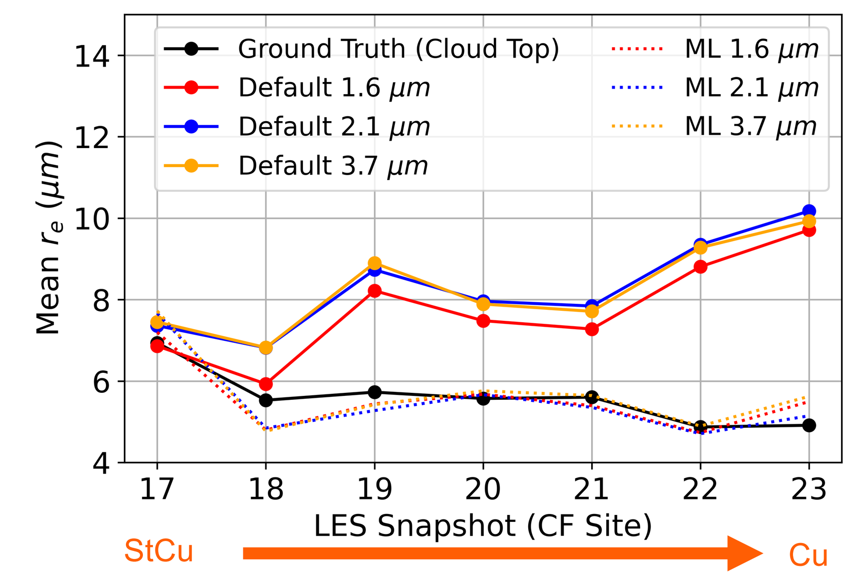


Methodology

- We train a neural network to predict cloud-top r_e using features from MODIS L2 data: $(\tau_c, H_\sigma, r_{e,1.6}, r_{e,2.1}, r_{e,3.7})$
- We apply 3D radiative transfer simulations to 840 stochastically generated cloud fields that assume quasi-adiabatic cloud microphysics to generate training data (Loveridge & Di Girolamo, 2024).
- Apply retrieval to MODIS data:
  1. 25° < Solar Zenith Angle < 35°
  2. Viewing Zenith Angle < 30°
  3. $\tau_c > 2$
  4. Oceanic, single-layer, non-precipitating liquid clouds.
  5. All MODIS r_e retrievals are valid.

Validation of machine-learning retrieval of r_e

- Biases against out-of-sample LES cloud fields from Shen et al., (2022) are eliminated by using the Machine Learning (ML) retrieval.



- Biases against in-situ measurements of shallow cumulus from CAMP²Ex RF 17 (Fu et al., 2022) are reduced by 60%.