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Beyond number concentration:
Application of adiabatic cloud models to infer complete vertical profiles of warm cloud microphysical properties

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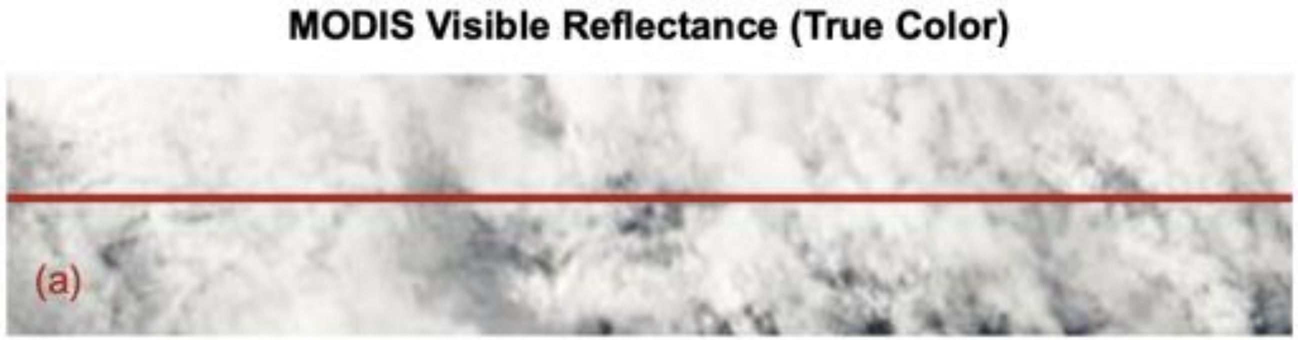
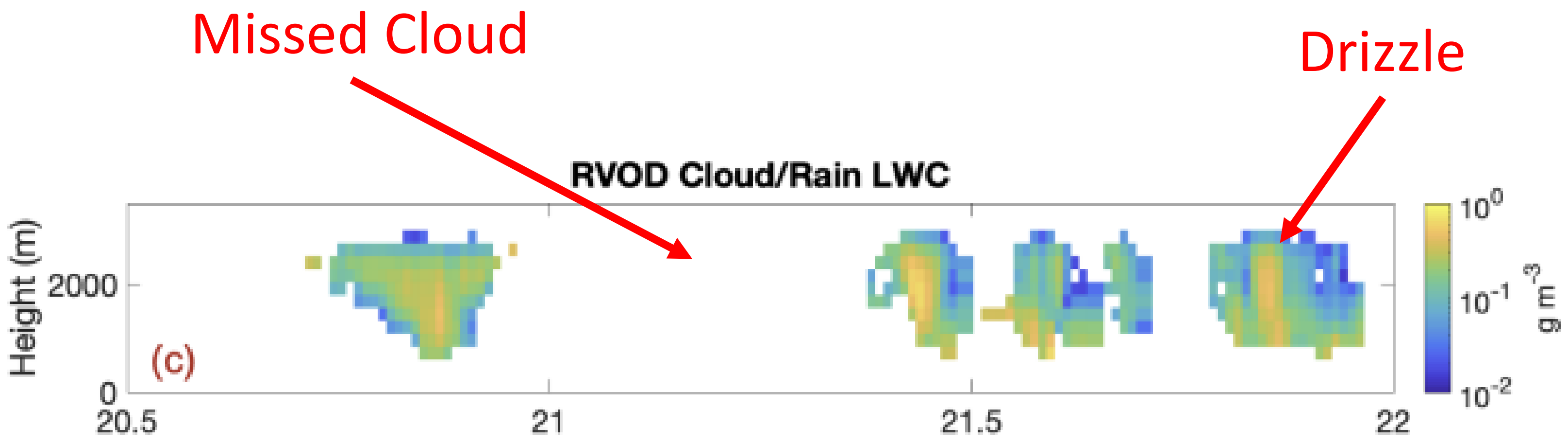
Existing Limitations



CWC-RVOD product:
Combined Radar + Visible Optical Depth
Leinonen et al., 2016



Key Points

1. Radar-based retrievals of low-cloud profiles have major deficiencies:
   - Missed detection
   - Precipitation contamination

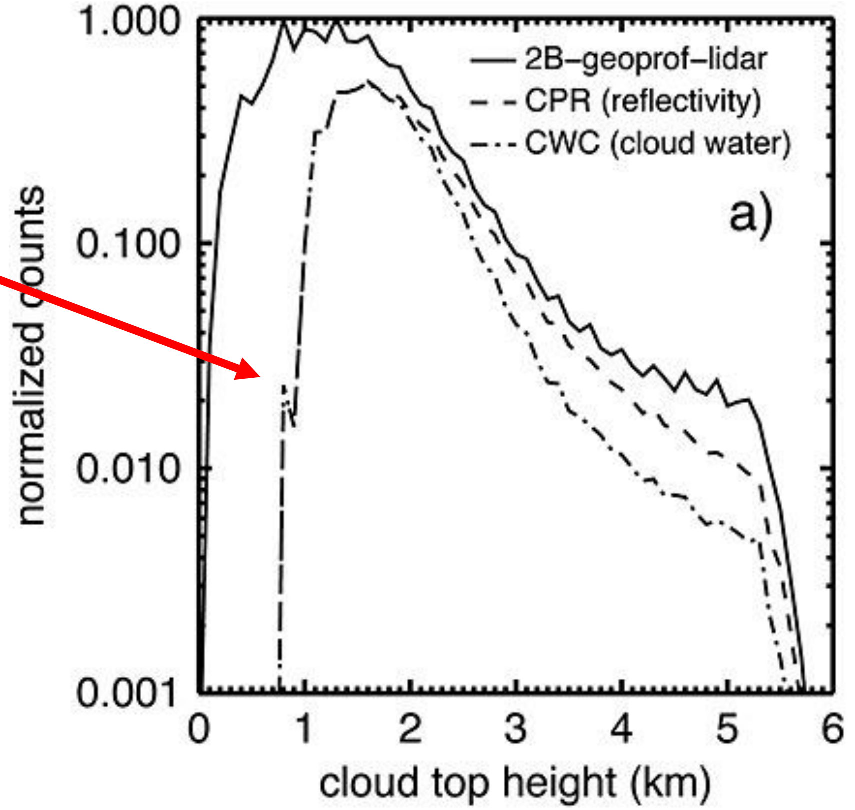
2. (Sub)adiabatic theory in good agreement with radar observations for non-precipitating clouds.
   - Only requires Vis/NIR observations to derive cloud profiles

3. Machine Learning (non-linear regression) can be used to exploit lidar observables and radar integral constraints to derive vertical profiles within reasonable uncertainties.
   - This works even when Vis/NIR observations are missing!

Problem #1

The CloudSat radar misses a large fraction of shallow warm clouds

~45% missed



Christensen et al., (2013)
https://doi.org/10.1002/2013JD020224

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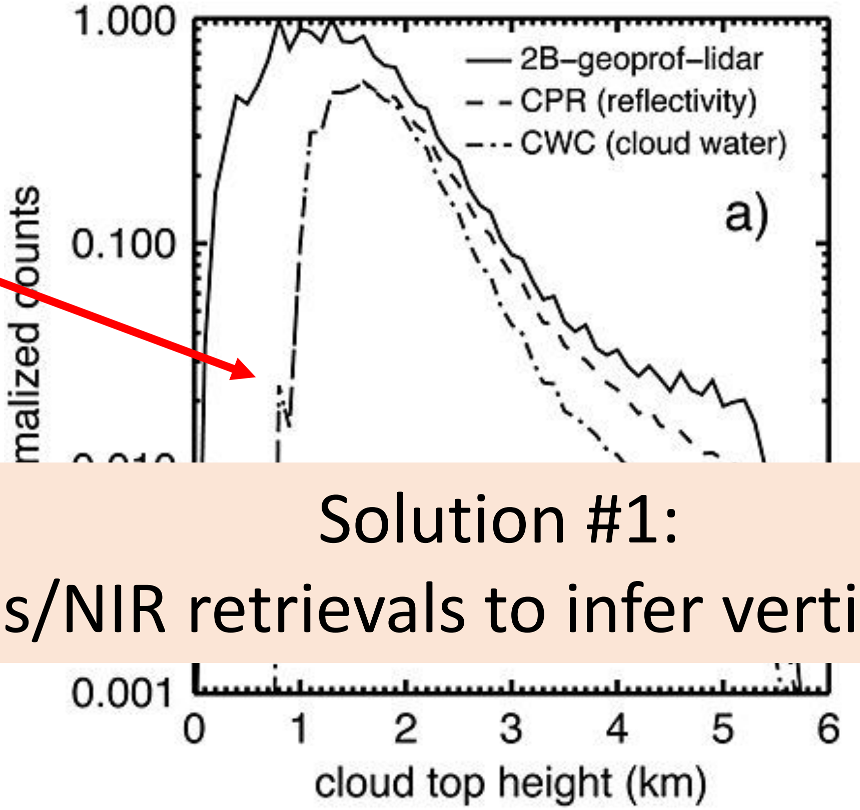

Solution #1:
Use Vis/NIR retrievals to infer vertical profiles

Christensen et al., (2013)
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Adiabatic Cloud Model

Adiabatic theory is widely used to translate:

$$\begin{matrix} \tau \\ r_e \end{matrix} \rightarrow \begin{matrix} LWP \\ N_d \end{matrix}$$

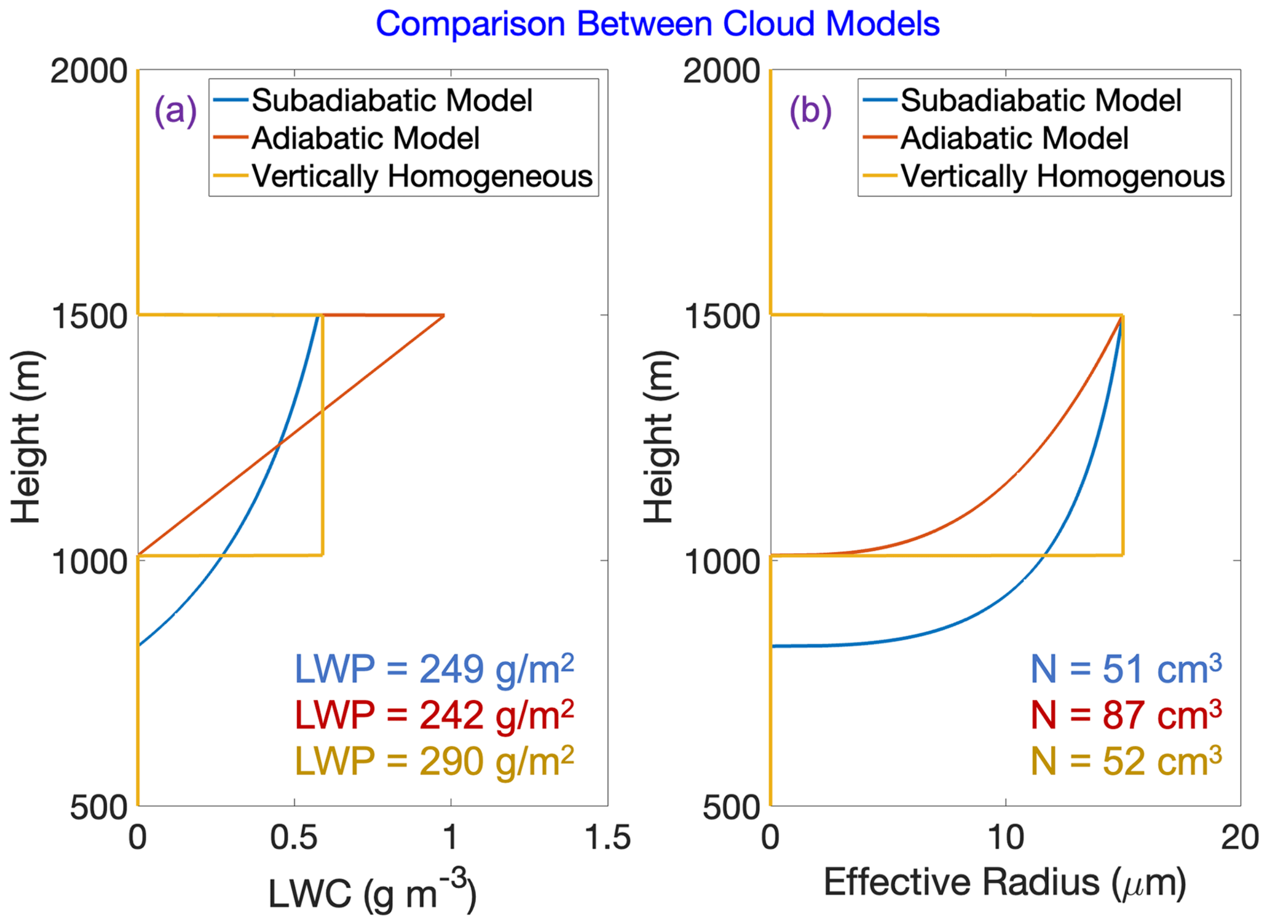
What's new here?

1. Use adiabatic theory to derive the complete profile - Not just number concentration.

2. Sub-adiabatic factor is a function of height above cloud base:

$$f_{ad}(h) = \frac{h_o}{h_o + h}$$

Adiabatic Cloud Model



Schulte et al., (2023)
https://doi.org/10.5194/amt-16-3531-2023

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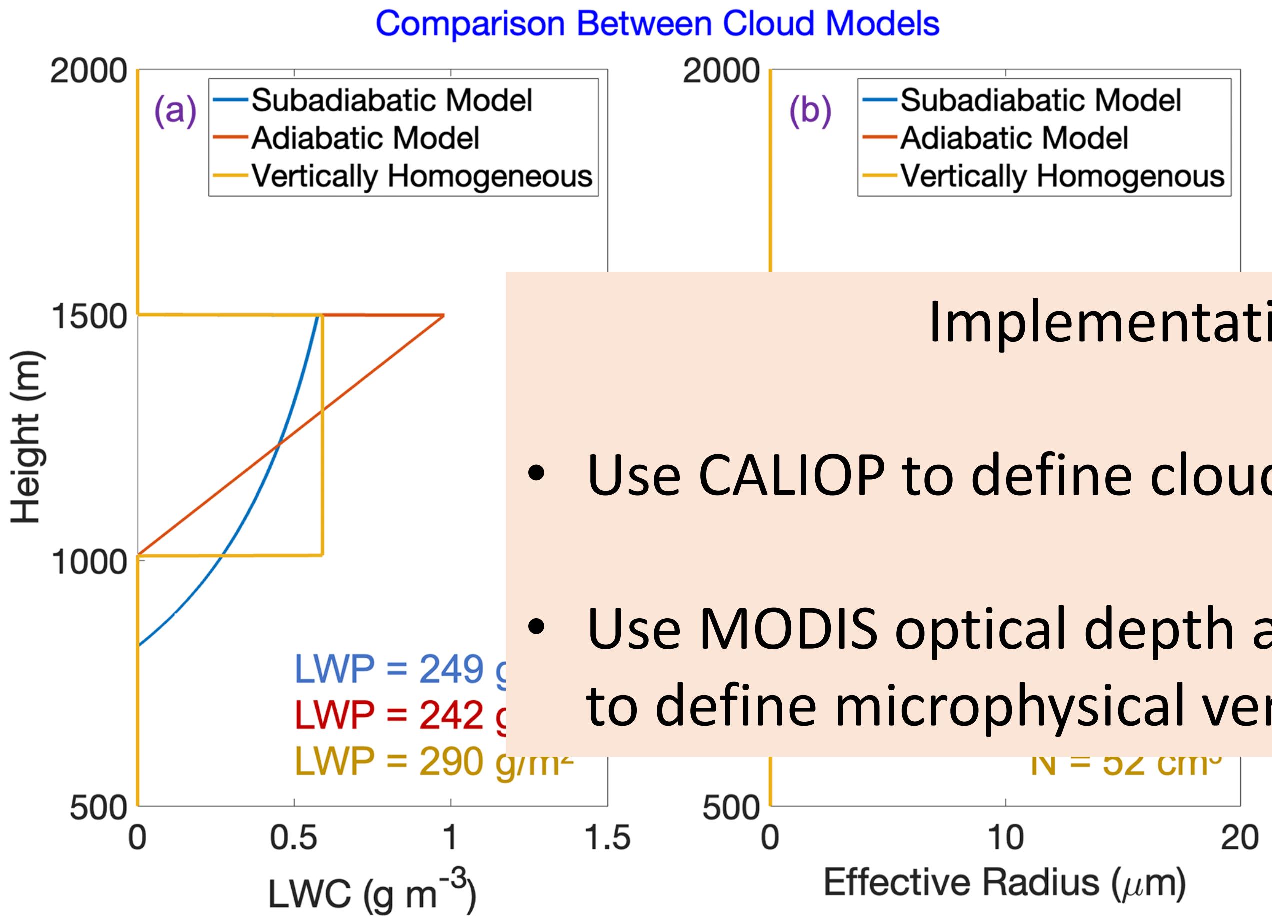

Implementation:

- Use CALIOP to define cloud top height.
- Use MODIS optical depth and effective radius to define microphysical vertical profile

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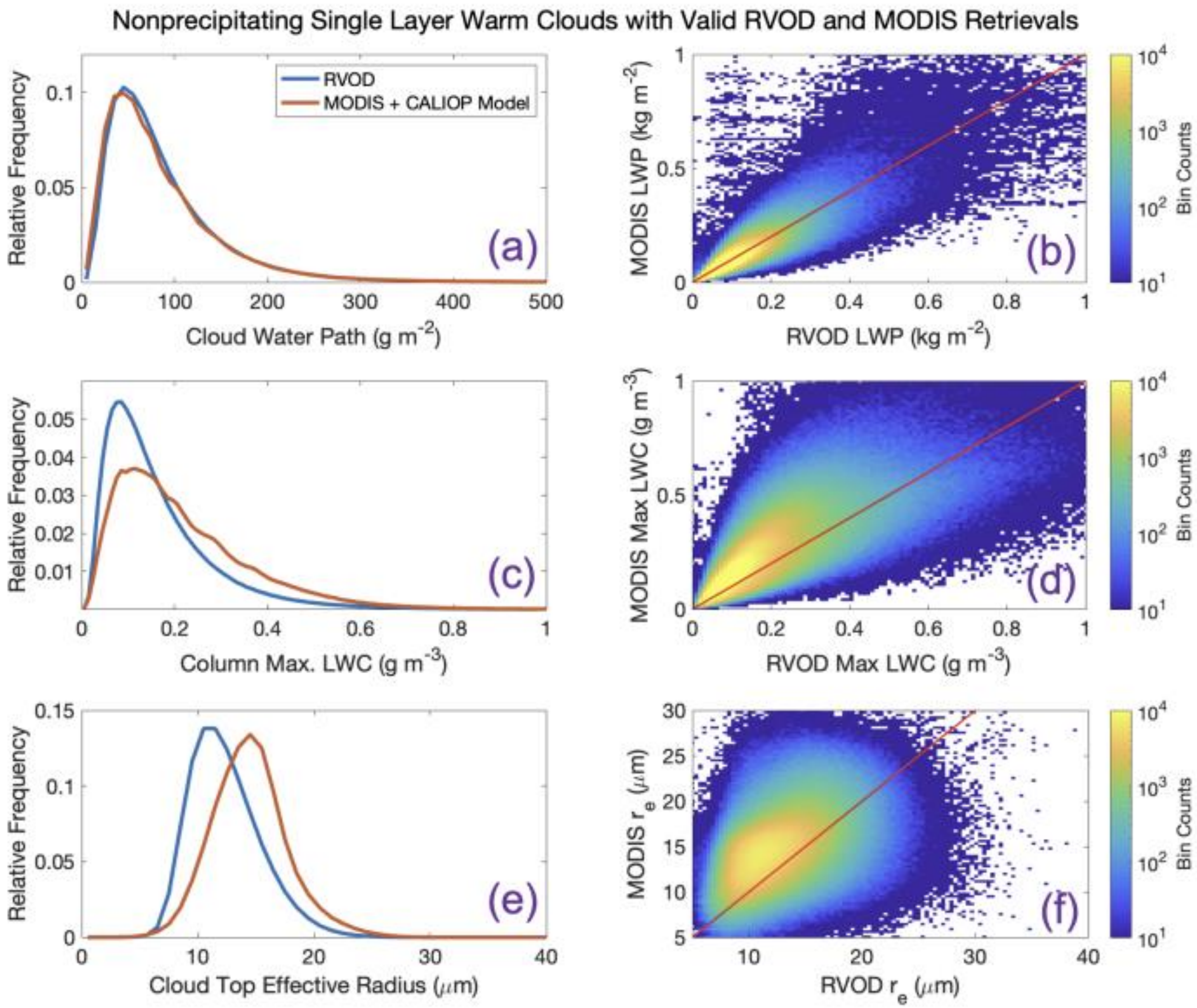
Validation of adiabatic Model



Example Solution #1 (missed clouds)

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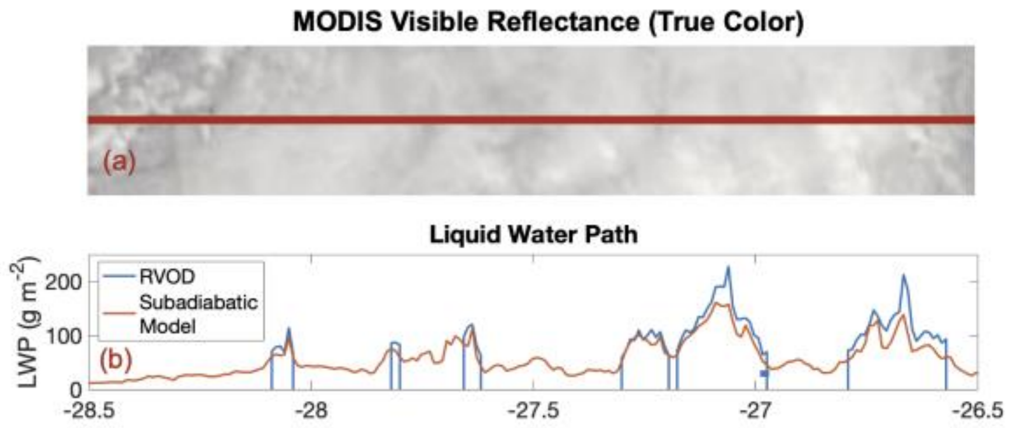

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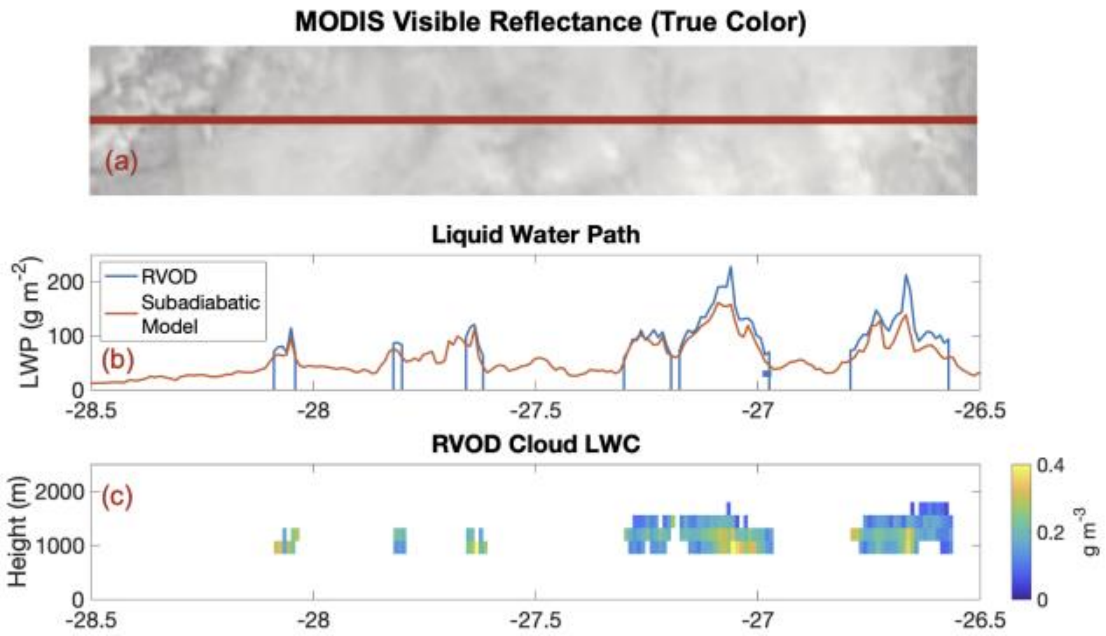

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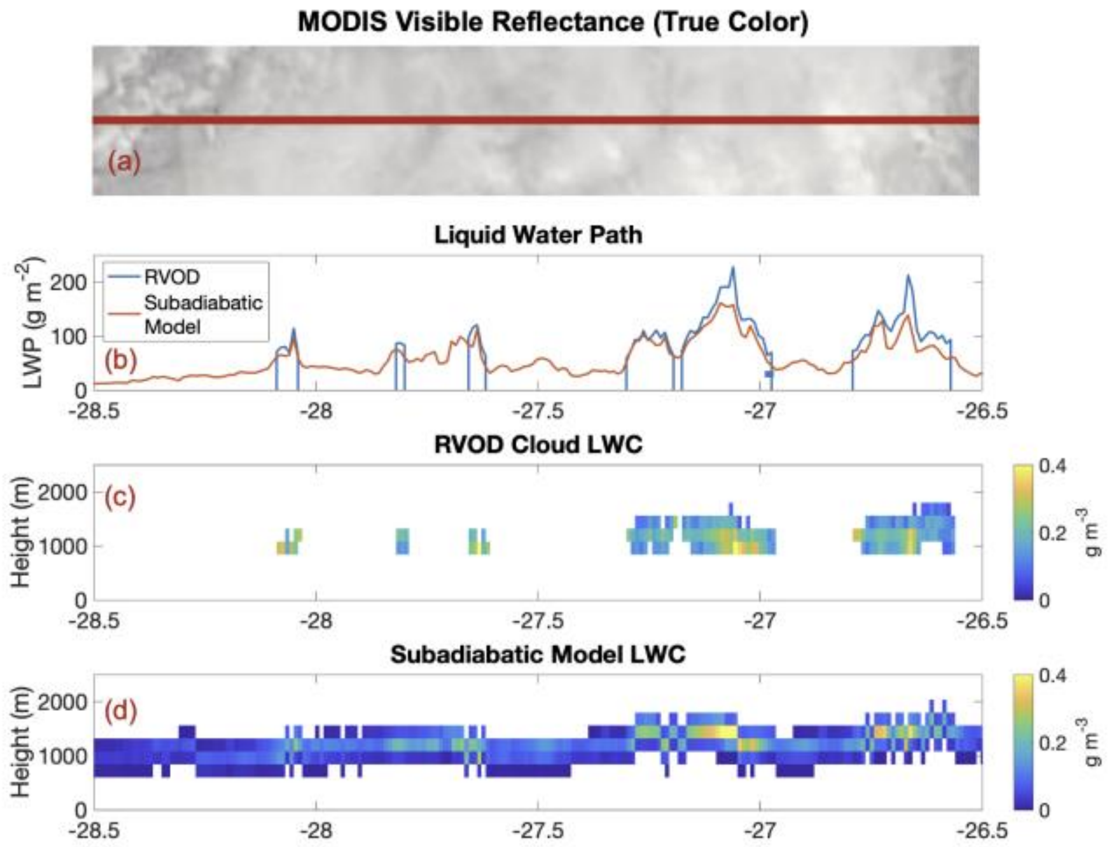

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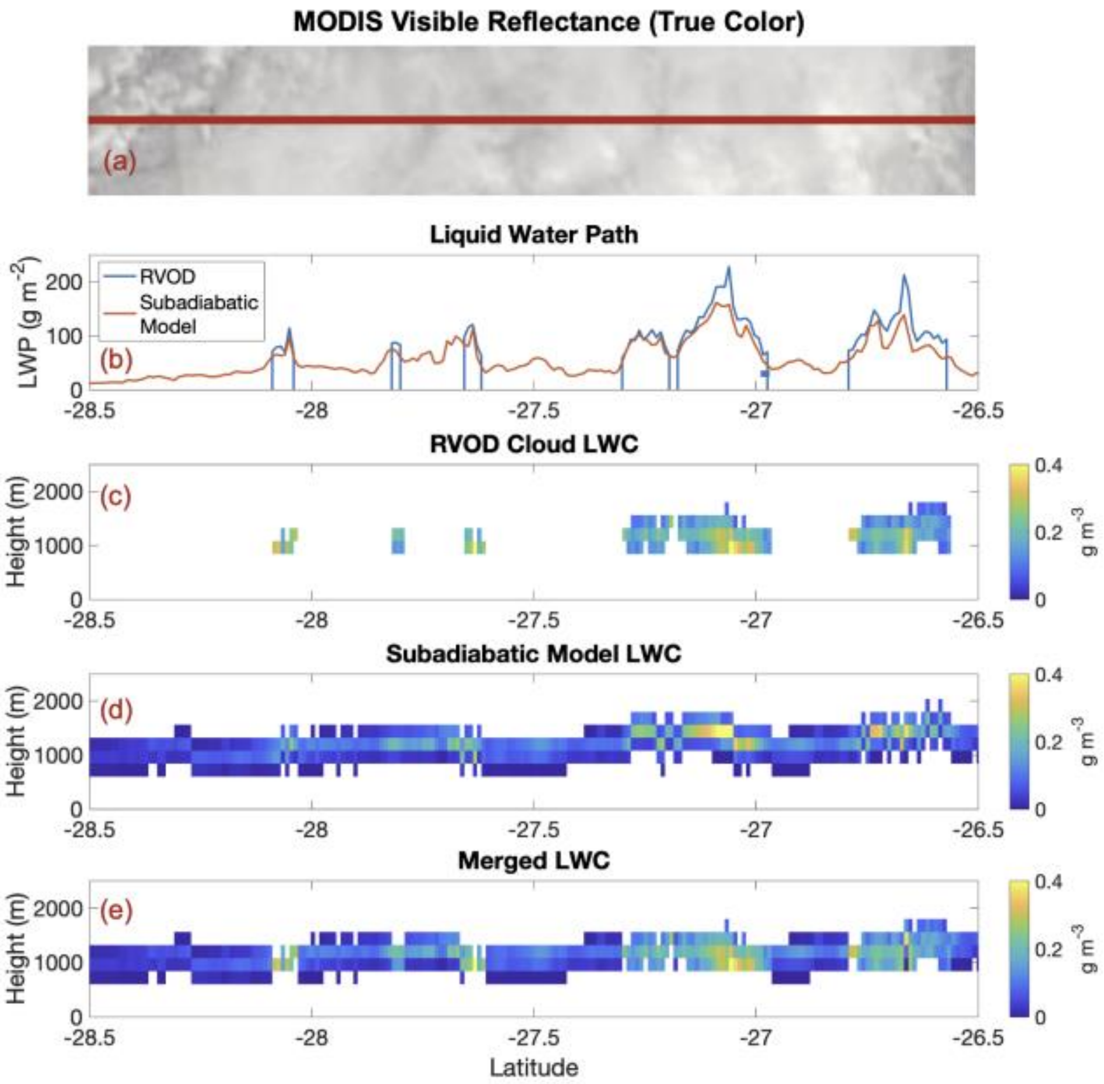
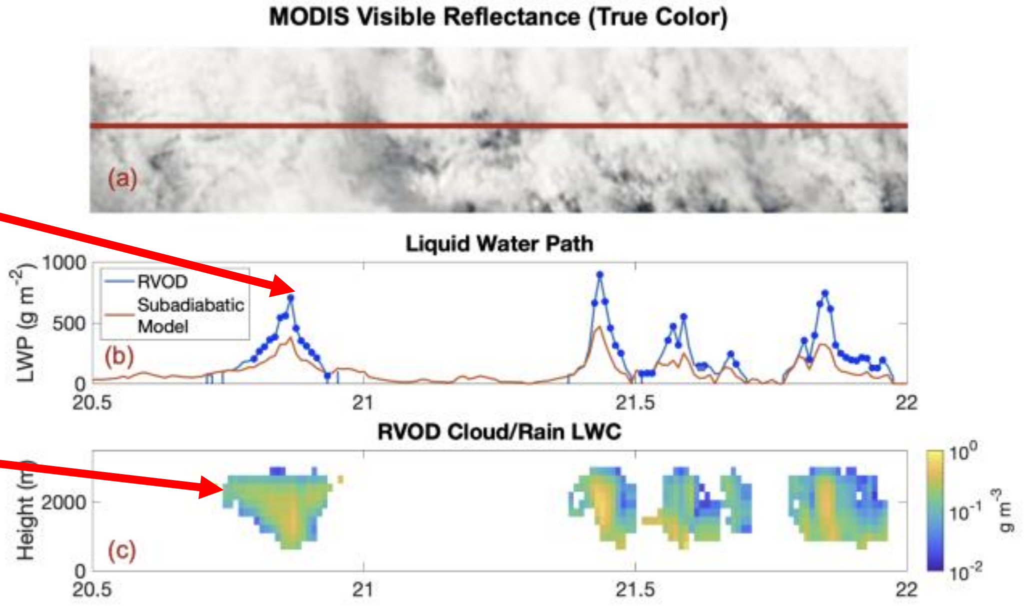


Problem #2

Radar retrievals misdiagnose precipitation as cloud water

Overestimated LWP

Drizzle Cells



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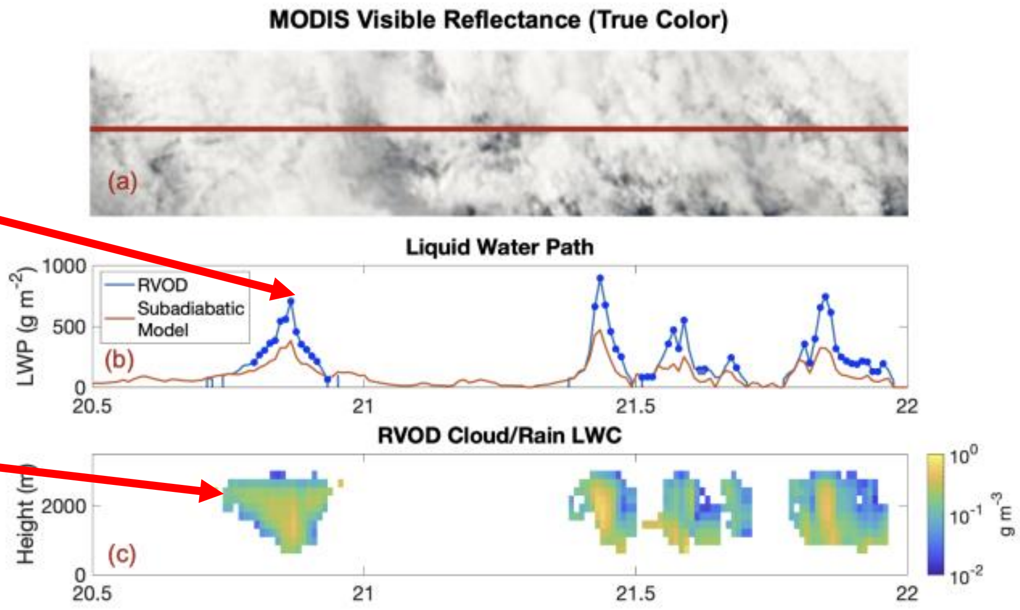

Solution #2:
Use Vis/NIR retrievals to infer vertical profiles

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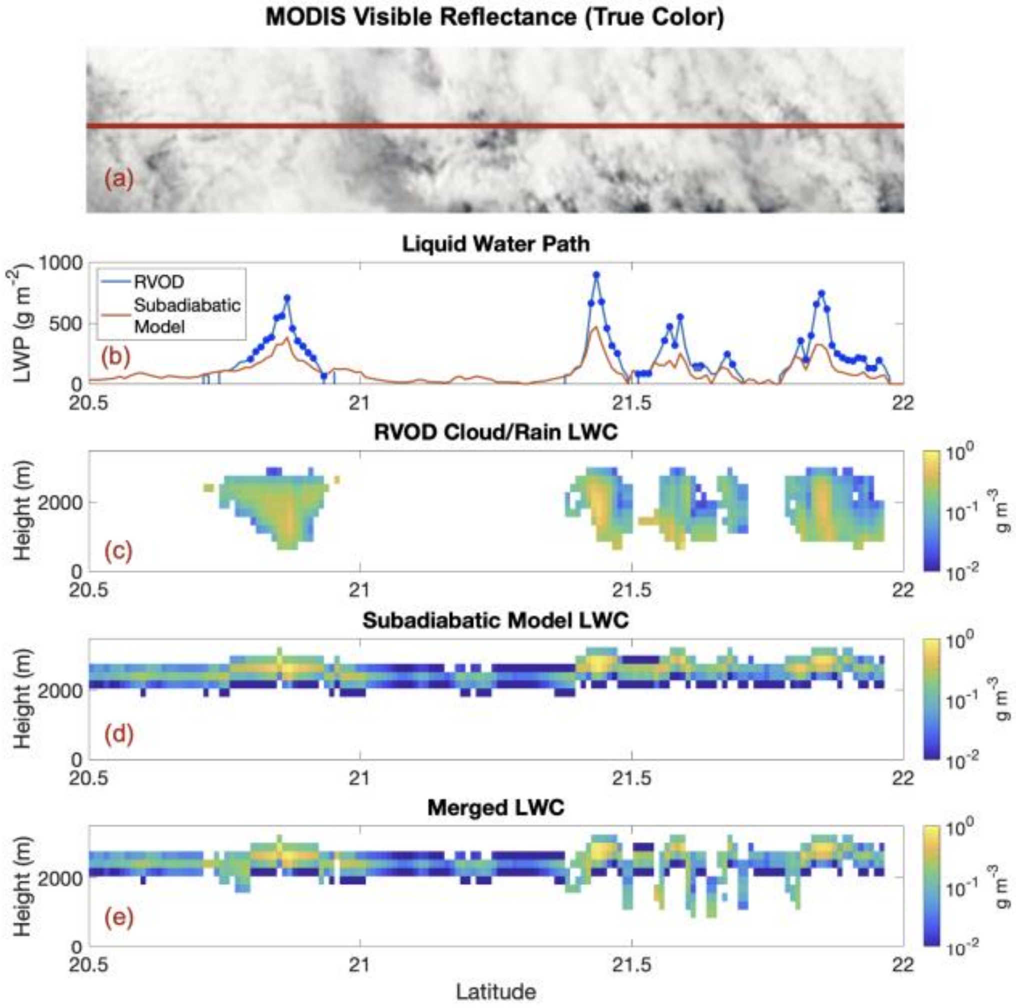

Problem #3

We have no Vis/NIR retrievals at night

OR

Vis/NIR retrievals fail

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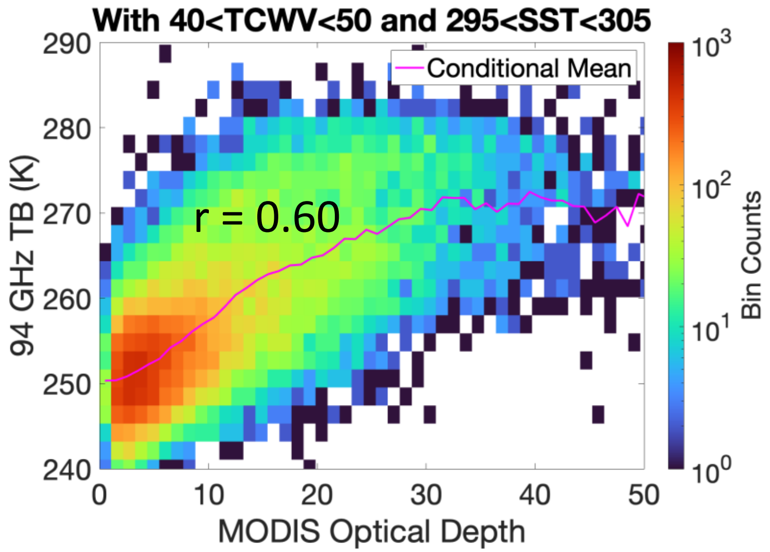

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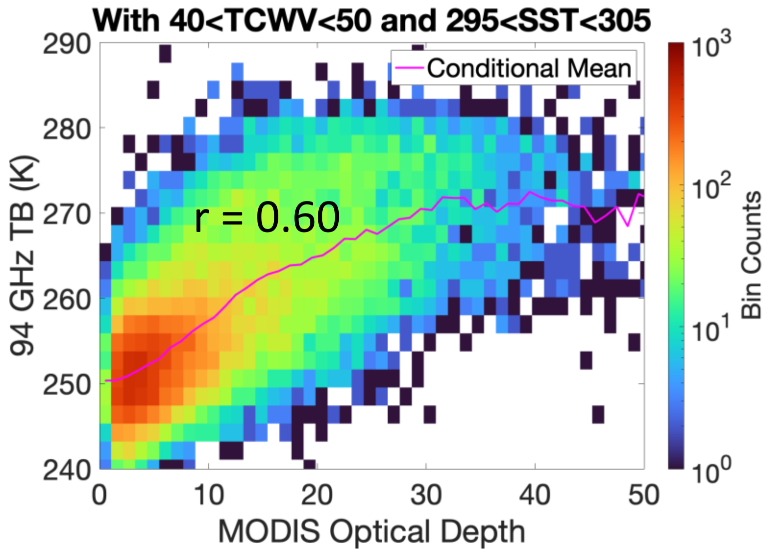

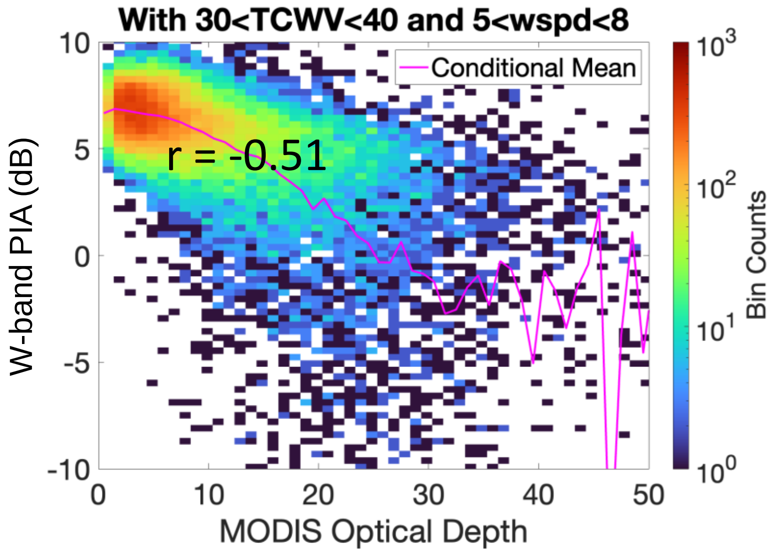

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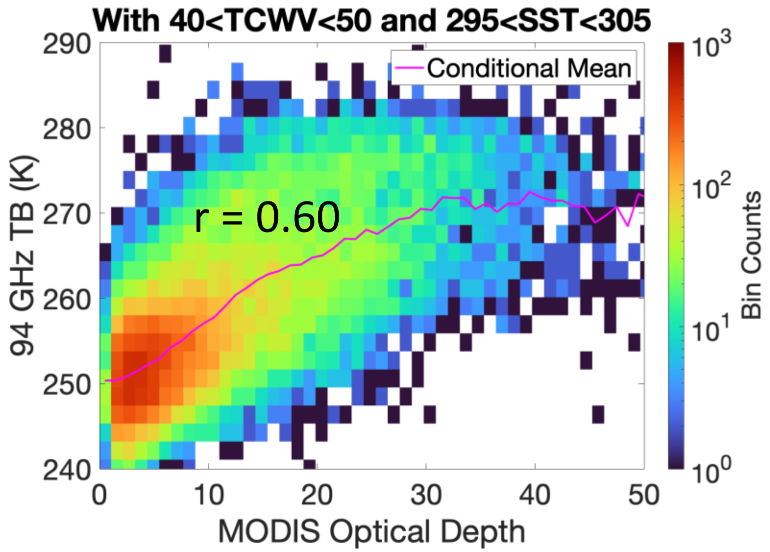

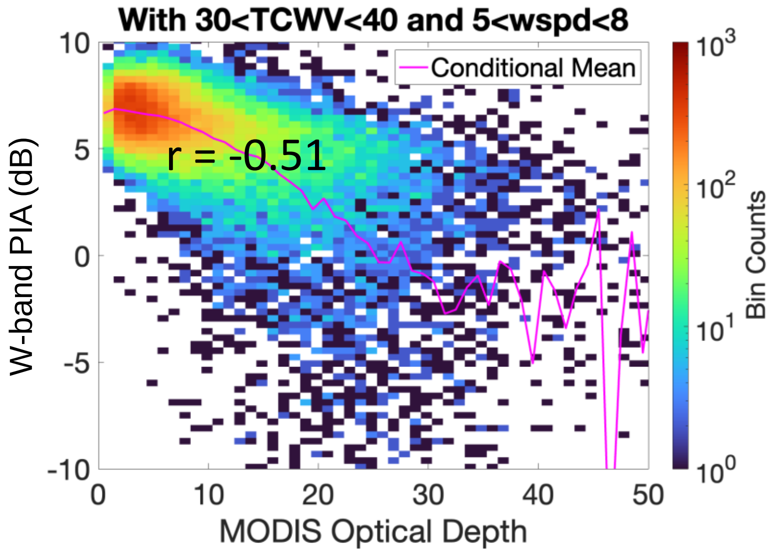

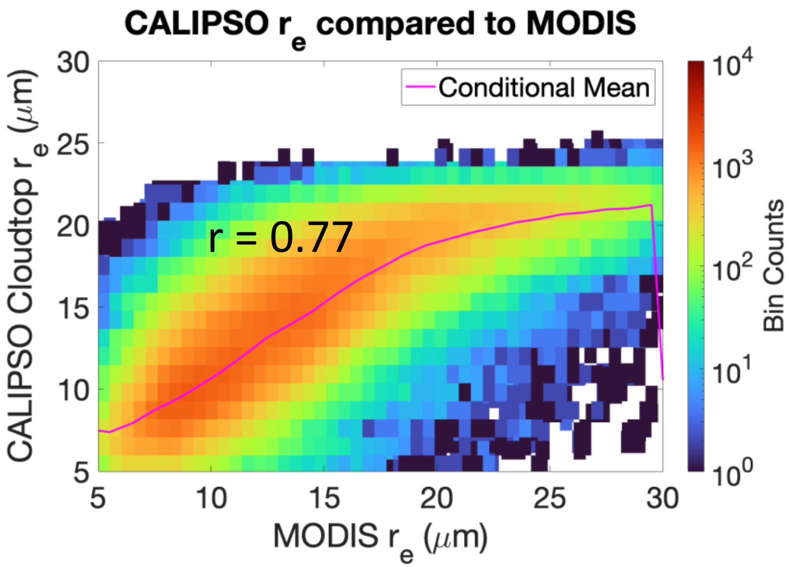

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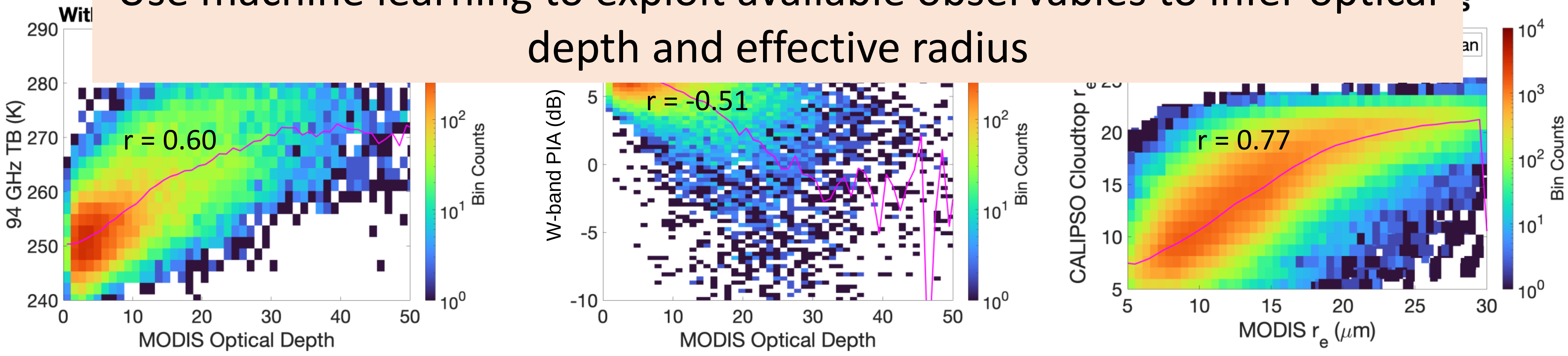
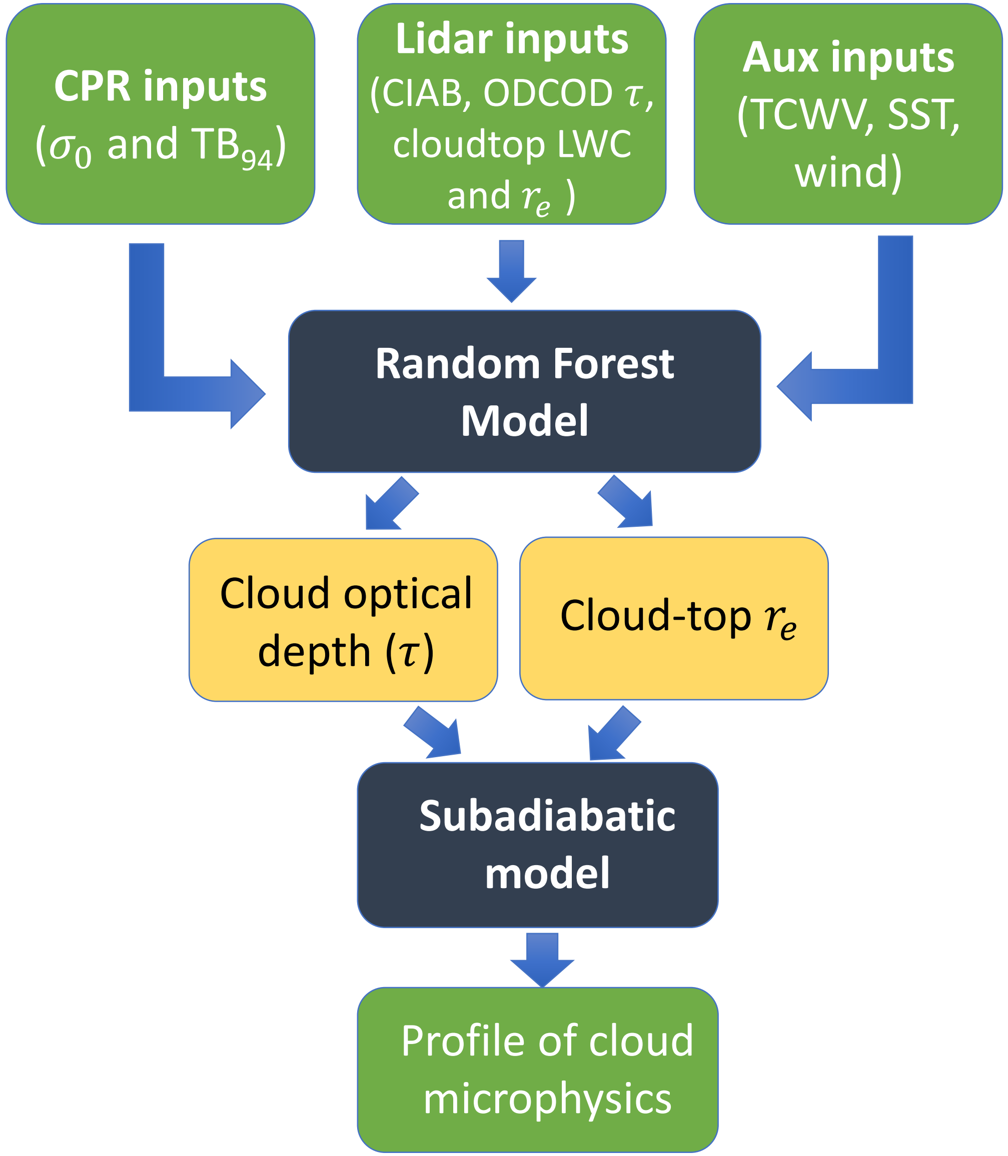
Solution #3:

Use machine learning to exploit available observables to infer optical depth and effective radius

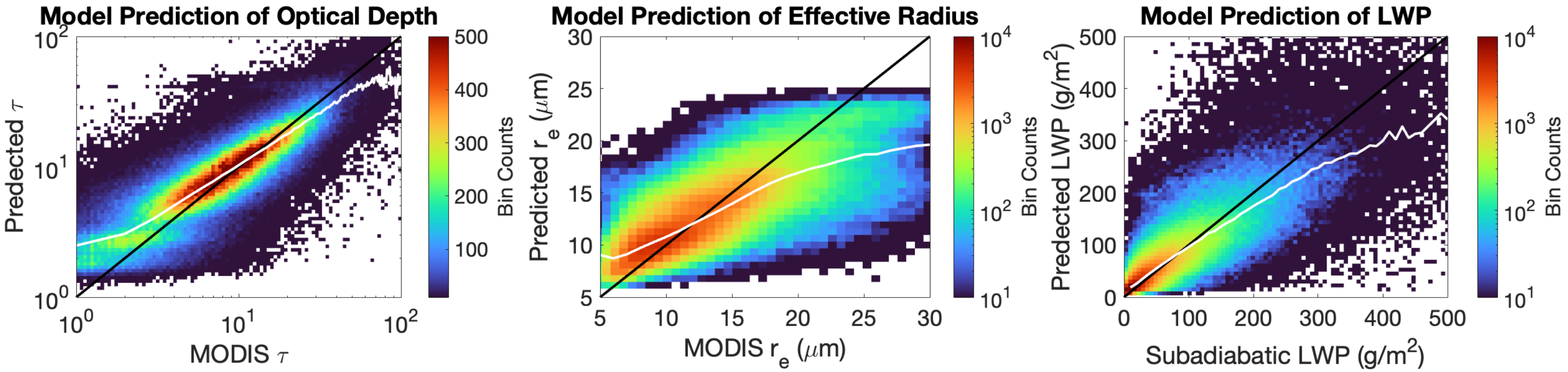


Machine Learning Approach

- Random forest regression model details:
  - Trained on Jan 2008, tested on February 2008
  - 50 trees
  - Ocean pixels only
  - Used Python’s scikit-learn package
- Model inputs:
  - CPR surface return (σ_0) and 94 GHz brightness temperature (TB_{94})
  - ECMWF environmental data: total column water vapor (TCWV), SST, and surface wind speed
  - CALIOP 532 nm column integrated attenuated backscatter (CIAB) and ODCOD optical depth
  - CALIPSO-based estimates of cloud top LWC and r_e from (Hu et al. 2021)



ML Model Performance

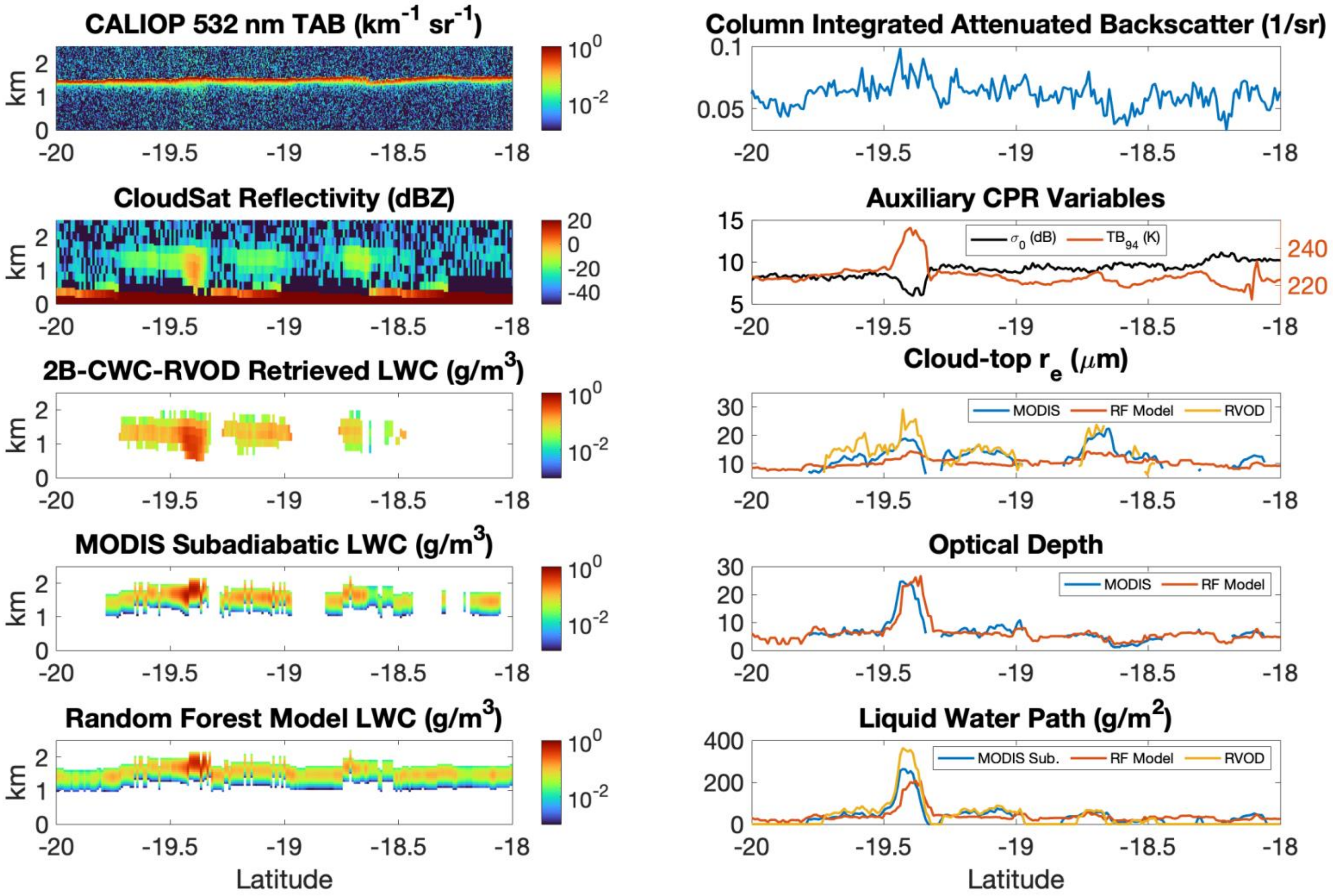


r = 0.77
MAE = 3.41
Bias = +0.22

r = 0.76
MAE = 2.22 μm
Bias = +0.05 μm

r = 0.81
MAE = 27.6 g/m^2
Bias = +2.1 g/m^2

ML Case Study



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