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INTRODUCTION

Bayesian cloud microphysical retrievals have promise for producing robust estimates of cloud particle size distribution properties, and for returning quantitative measures of uncertainty (Posselt and Mace, 2014; Posselt et al., 2017). Bayesian methods also yield an assessment of information contained in observations from one or more different measurement platforms, and can be used to establish measurement accuracy criteria.

The ARM program has invested in both measurement and modeling resources:

- Active and passive remote sensing instruments
- Systematic large eddy simulation (LES) modeling activity

Project goal: develop a robust cloud property retrieval analysis framework suitable for uncertainty and multiple instruments, regions, and application to seasons.

OBS AND RETRIEVED VARIABLES

Model output from DHARMA (Lee et al. 2019) simulation of a CAP-MBL case 22 Nov 2009 (Remillard et al. 2017)

- Ka- and W-Band reflectivity (3 dB uncertainty)
- Ka- and W-Band Doppler velocity (2 m/s uncertainty)
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Retrieve LWC, Nt, & Re for cloud and rain with gamma PSD • Modal diameter (D_i)

- Modal number (N_i)
- PSD width (*alpha_i*)

$$(D) = N_i \left(\frac{D}{D_i}\right)^{\alpha_i} \exp\left(-\frac{D}{D_i}\right)$$

RETRIEVAL METHODOLOGY

Retrievals seek the most likely solution, given observations and prior knowledge.

The most complete solution provides not only the optimal solution, but also the uncertainty.

Bayesian inverse methods formalize the obs - forward model – retrieval relationship, and determine the solution properties for given obs, forward model(s), and prior.

Markov chain Monte Carlo Method: Construct a Markov chain that samples $p(\mathbf{x}|\mathbf{y})$. A random walk guided by information from observations

- Prior $p(\mathbf{x})$: Truncated Gaussian based on in-situ obs of cloud PSD properties within shallow cumulus
- Observation likelihood $p(\mathbf{y}|\mathbf{x})$: Gaussian uncertainties

$p(\mathbf{x} | \mathbf{y}) \propto p(\mathbf{y} | \mathbf{x}) p(\mathbf{x})$

MCMC produces a sample of the probability distribution of retrieval solutions, from which the optimal estimate, and its uncertainty, may be computed.



Retrieval assumes the arbitrarily complex DSD can be approximated via a two-mode (non-precipitating and precipitating) gamma distribution of drops. This inevitably leads to errors in the retrieval.

Goal: estimate uncertainty in radar Doppler moments (e.g., reflectivity, mean Doppler velocity, spectrum width, skewness, and kurtosis) caused by the gamma DSD assumption.

Methodology:

$$M_x = \int_0^{D_{max}} D^x N(D) d$$

Constrain the 6 parameters of the 2-mode gamma DSD using moments of the "true" DSD, where moments are defined as

Uncertainty in all moments is assumed to be 1 dB. Use MCMC to estimate the PDF of the PSD parameters given the bin DSD as "observations".

The prior distribution is assumed to be uniform in $\log_{10} N_0$, D_0 , and alpha for each mode, with a restriction that the cloud mode has a smaller effective radius than the precipitating (rain/drizzle) mode.



- median, mode (central tendency); and std dev, IQR, and percentiles (uncertainty estimates)
- constraint dependent on how many Doppler moments are used.
- diameter; cloud number > rain number), and these are easy to apply in an MCMC framework. **Future Work**
- We are currently retrieving LWC, number, and size from ARM ENA observations
- Use retrieved cloud properties to study drizzle formation processes in shallow marine clouds

ACKNOWLEDGEMENTS AND REFERENCES

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• MCMC produces a sample of the full PDF of the solution space: allows estimate of mean, ARM radars place a primary constraint on cloud and precipitation mode PSD properties, with

• Use of Z, Vd, spectrum width, and kurtosis result in strong constraint on LWC, size, and number. Effective retrieval requires imposition of physical relationships (e.g., cloud diameter < rain

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