Bayesian Retrievals of Vertically Resolved Cloud Properties

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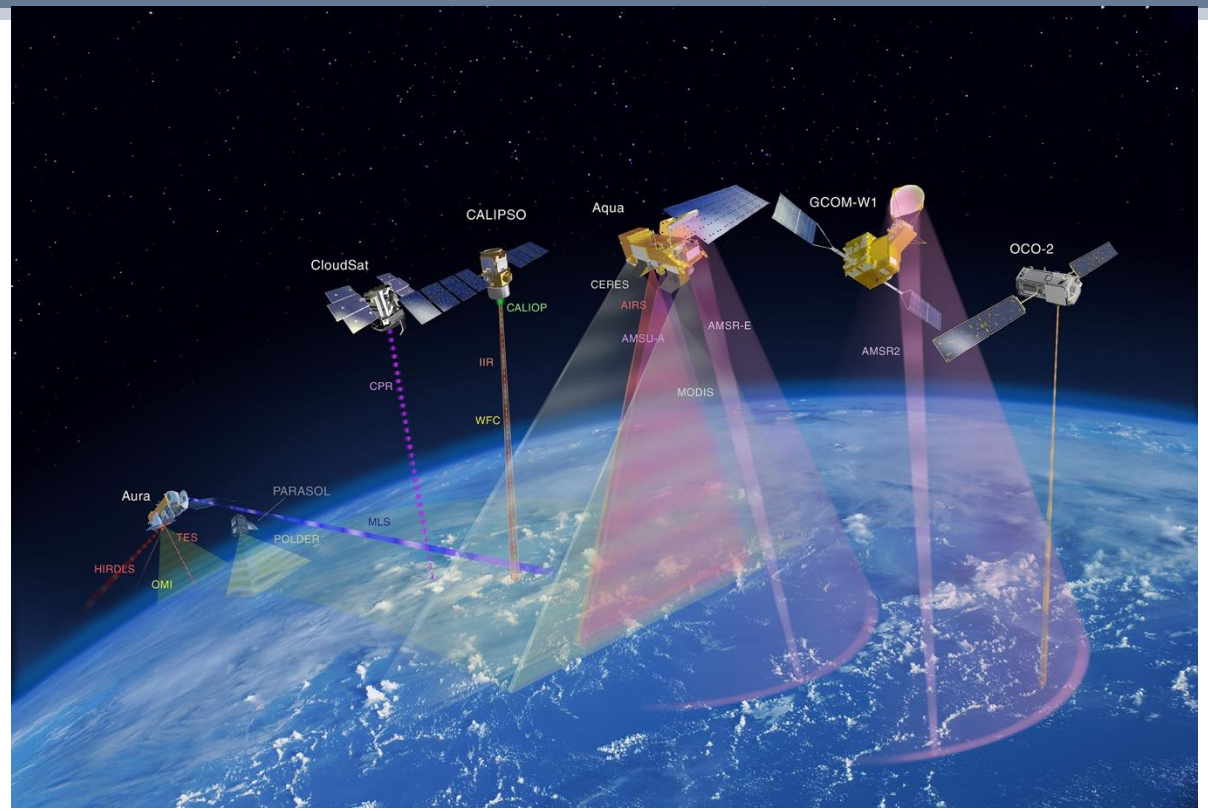
NASA Aerosols, Clouds, Ecosystems (ACE) NNX15AK17G

A-Train Advances for Cloud Profiling

- Instrument synergy
  - Cloud profiling radar
  - Cloud and aerosol lidar
  - High resolution visible, near-IR, IR imaging
  - Thermodynamic sounding (cloud context)
- Global observations
- What is next?
  - Time dimension, processes?
  - Additional measurements?
- Questions:
  - **How much information do current measurements provide?**
  - **How to quantify measurement requirements for next generation systems?**



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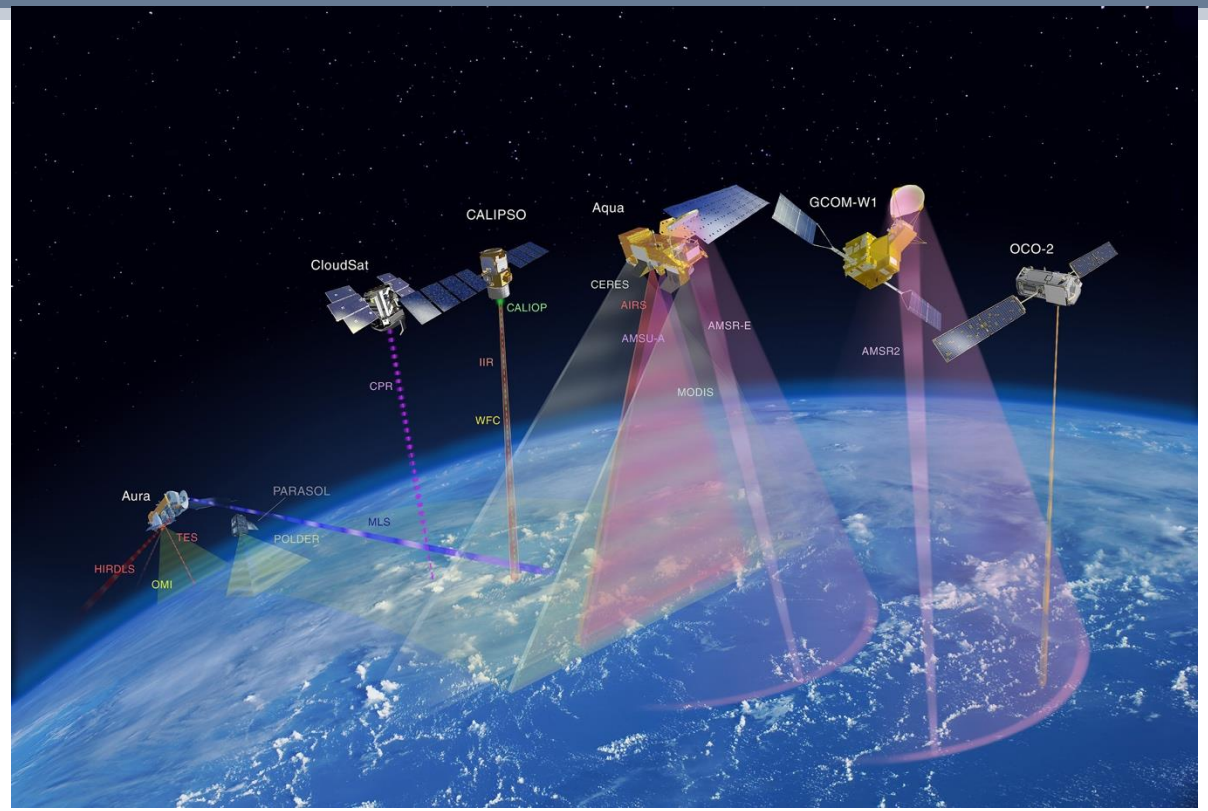

Observing System Simulation Experiments

- Traditionally: evaluation of potential impact of new observations on a NWP forecast (Hoffman and Atlas, 2016; BAMS)
- Fundamentally: quantify information in a future observing system
- Consider a spectrum of OSSEs:
  - Do measurements provide enough information to estimate geophysical quantities of interest? What are the uncertainties? **(retrieval OSSE)**
  - Which measurements are needed to characterize observe a process (or set of processes) **(process OSSE)**
  - Which observations should be made to constrain climate forcing and response **(climate OSSE)**
  - How does assimilation of new observations affect/improve a weather forecast? **(forecast OSSE)**

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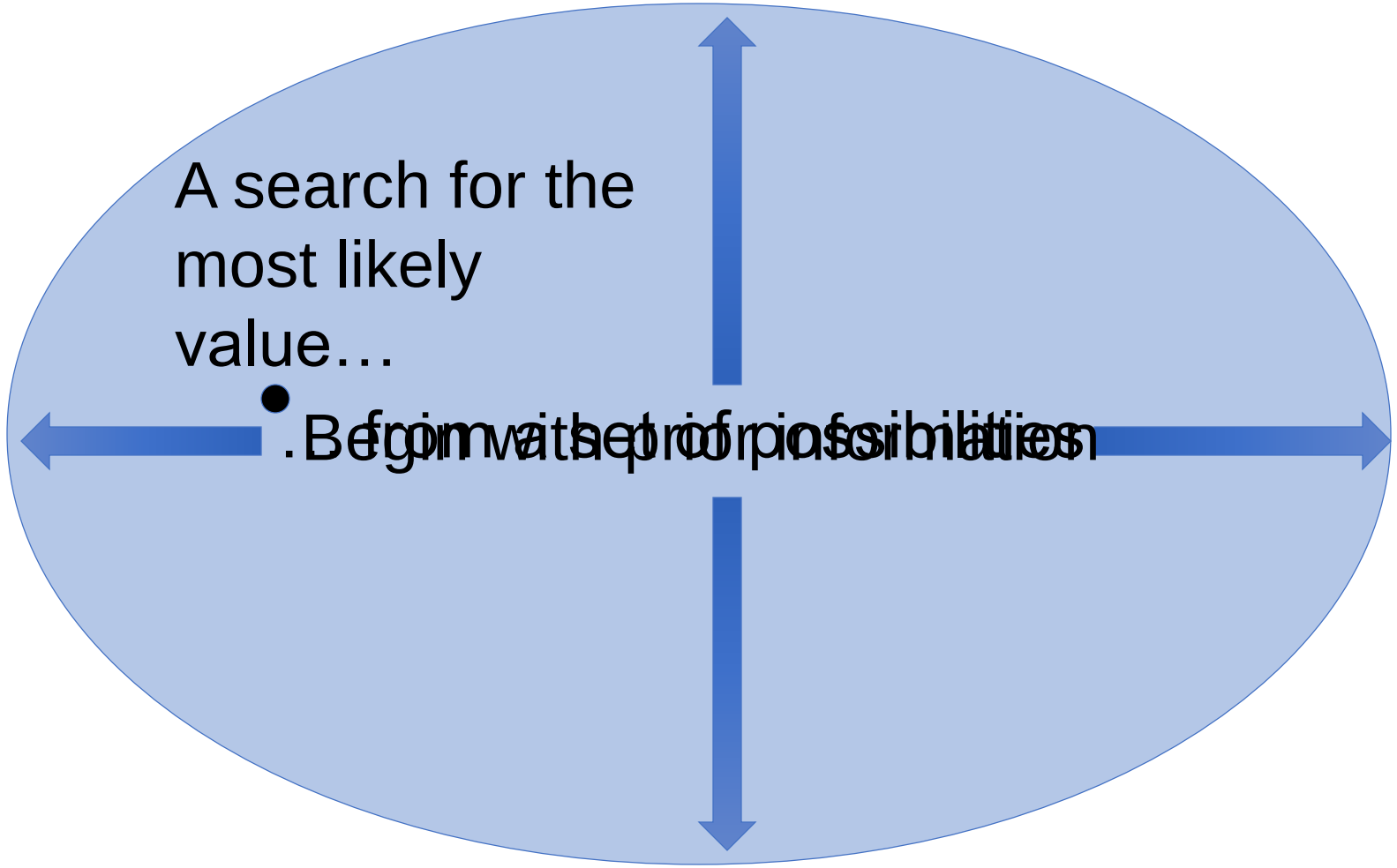
Quantifying Information

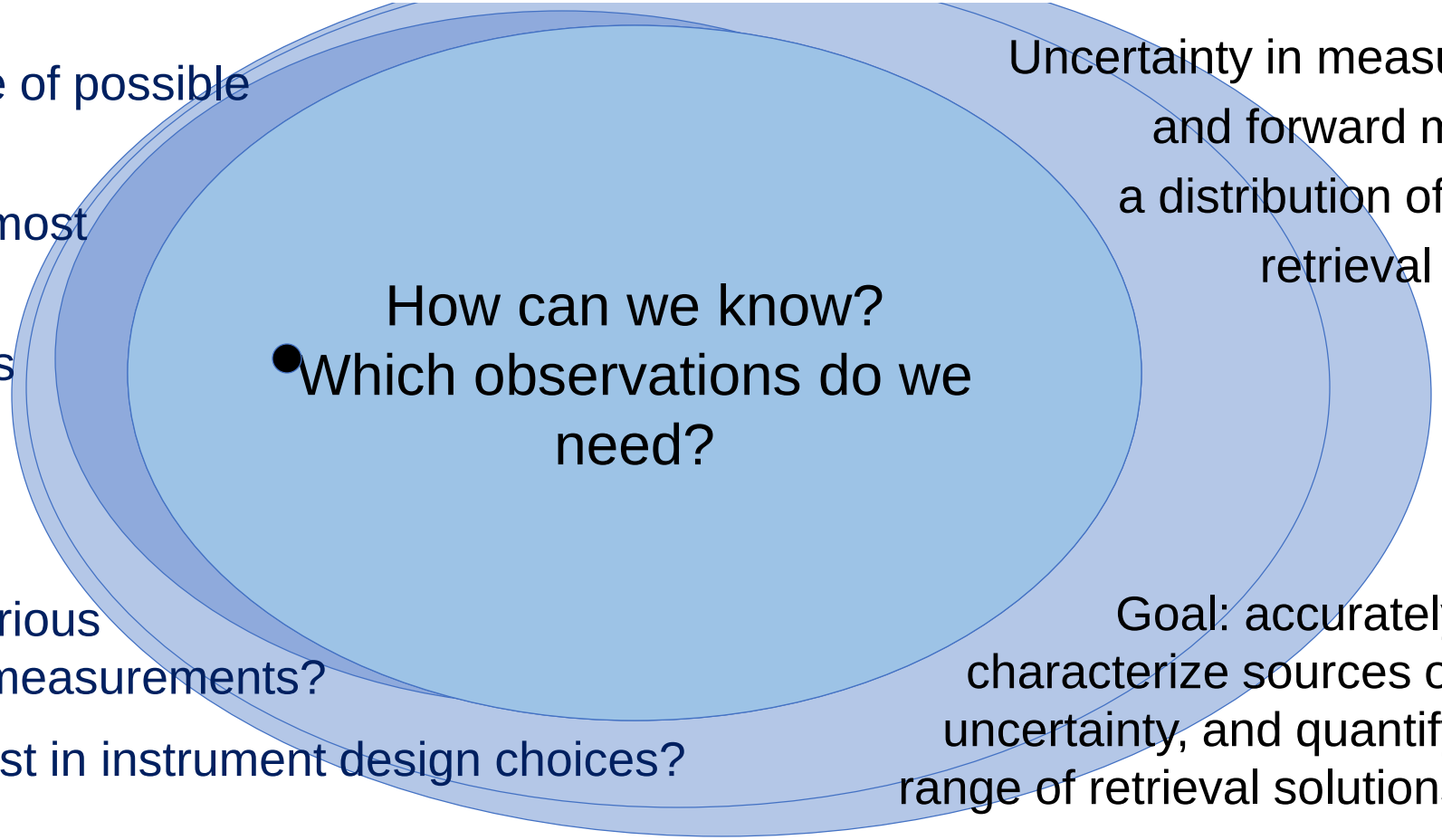
- Think about retrievals



Quantifying Information

Specific application: vertical profiles of cloud properties

- What is the range of possible solutions?
- Is there a single most likely solution?
- Is there skewness (bias)?
- How much information is contributed by various combinations of measurements?
- What is gained/lost in instrument design choices?



Uncertainty in measurements and forward models → a distribution of possible retrieval solutions

Goal: accurately characterize sources of uncertainty, and quantify range of retrieval solutions

Bayesian Perspective

Goal: understand the range of retrieval solutions (uncertainty quantification) and the contribution of various measurements

The solution *is* a distribution of possible outcomes: a PDF

- Can be described using probability theory – what is the likelihood of a particular state, given everything we know about the system of interest?
- Quantify the information we already have (prior, $p(\mathbf{x})$)
- Quantify the influence of new information (observations/likelihood, $p(\mathbf{y}|\mathbf{x})$)
- Quantify the range of solutions, given these pieces of information (analysis/retrieval/posterior, $p(\mathbf{x}|\mathbf{y})$)

$$p(\mathbf{x}\,|\,\mathbf{y}) \mu\ p(\mathbf{y}\,|\,\mathbf{x})p(\mathbf{x})$$

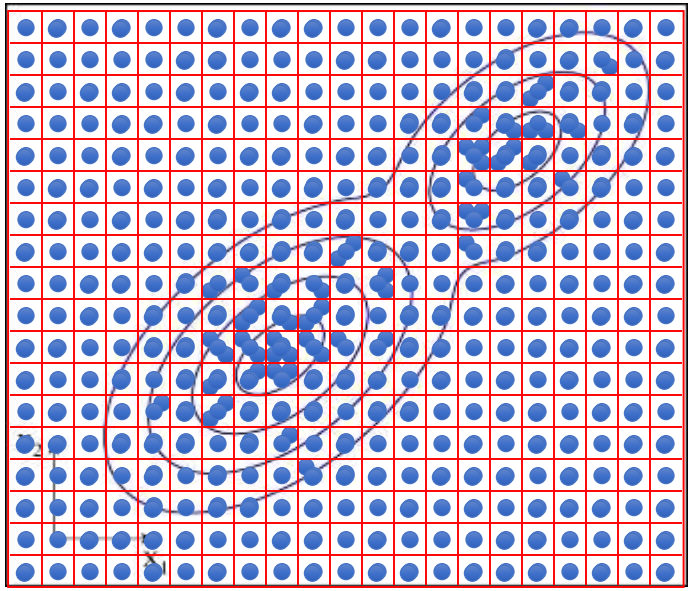
Bayes theorem combines the available pieces of information to produce a retrieval solution

Obtaining the Bayesian Solution

Goal: estimate $p(\mathbf{x}|\mathbf{y})$ given $p(\mathbf{y}|\mathbf{x})$

Options:

- Assume a distribution for each source of information
- Compute by brute force
- Random sample (Monte Carlo)
- Construct a Markov chain that samples $p(\mathbf{x}|\mathbf{y})$



Markov chain Monte Carlo:

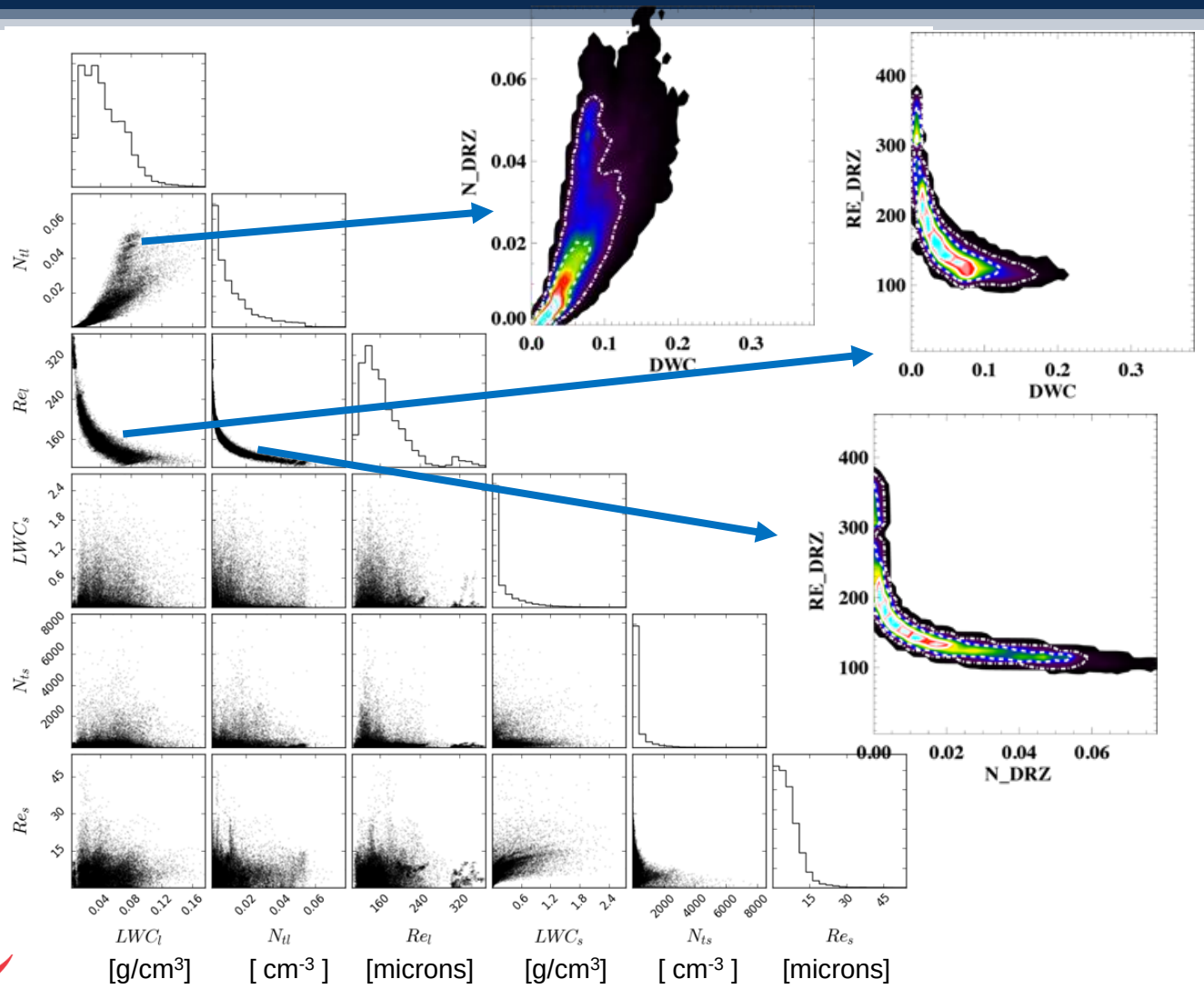
- Produces a sample of $p(\mathbf{x}|\mathbf{y})$
- Avoids states that provide a poor fit to observations (low likelihood $p(\mathbf{y}|\mathbf{x})$)
- Flexible probability distributions (no need for Gaussian assumption)

$$p(\mathbf{x}\,|\,\mathbf{y}) \mu\ p(\mathbf{y}\,|\,\mathbf{x})p(\mathbf{x})$$

Posselt et al. (2008, JGR), Posselt and Mace (2014, JAMC), Posselt et al. (2015, MWR), Posselt et al. (2017, JAMC)

Posterior Distribution $p(\mathbf{x}|\mathbf{y})$, Single Level

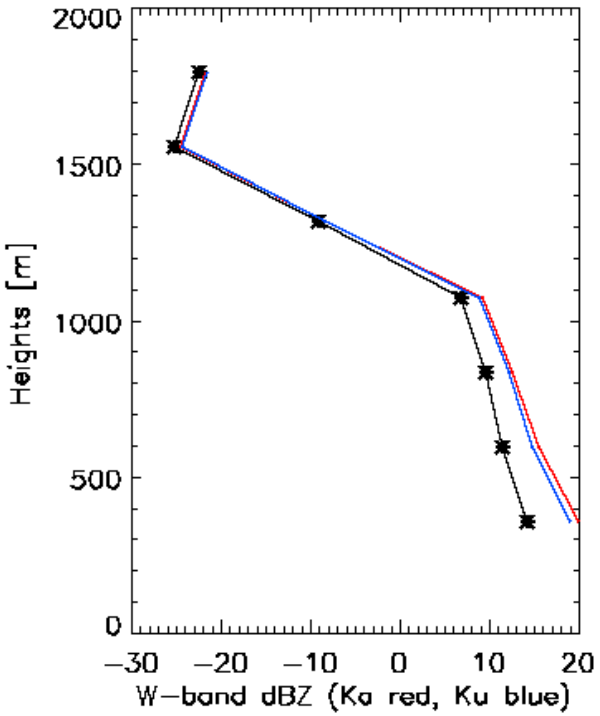
W-Ka 12 May 2014, level 3 from top

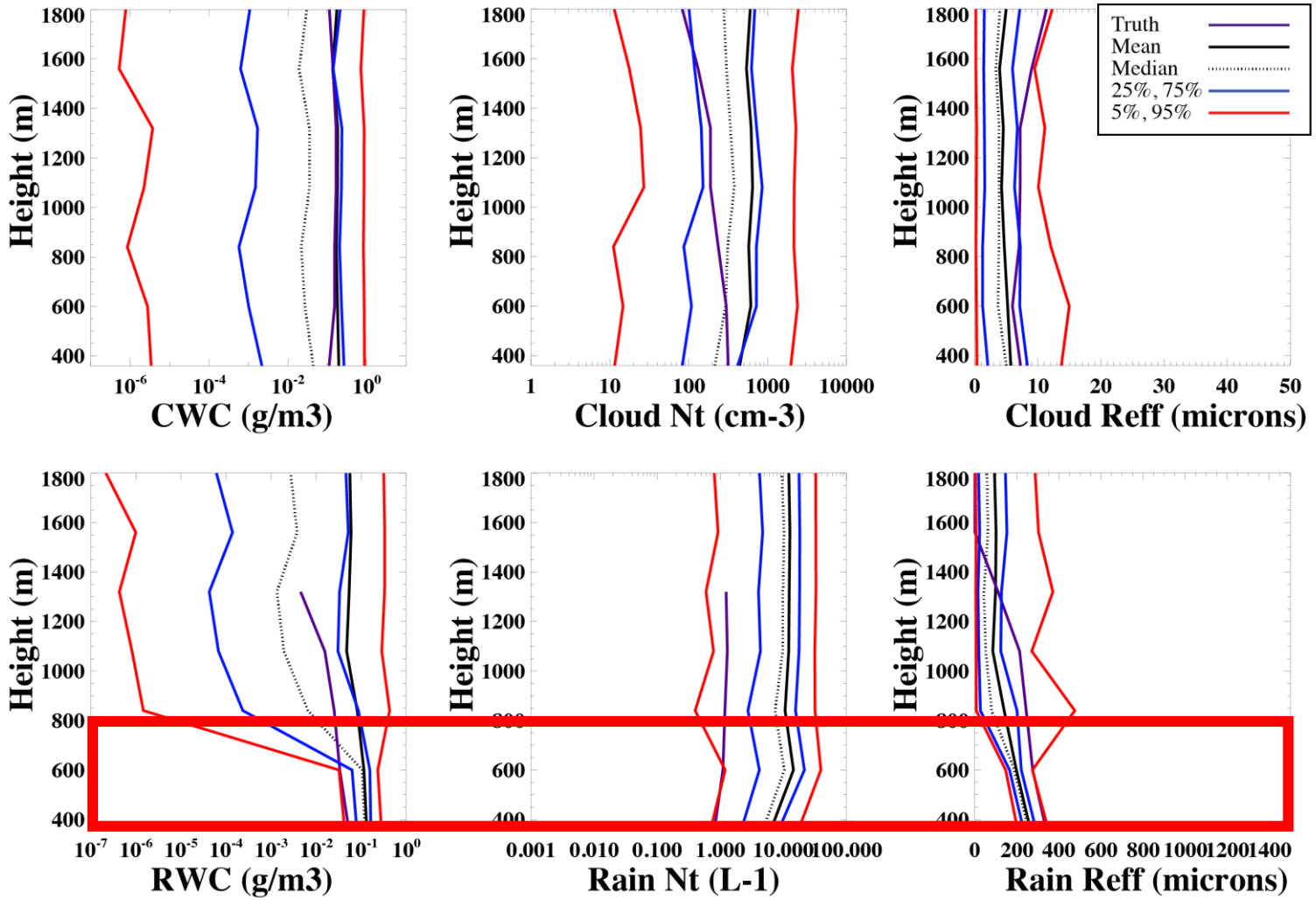


Bayesian retrieval:

- Joint PDF of all cloud properties at every level
  - Uniqueness
  - Correlation
  - Variance (uncertainty)
  - Skewness (bias)

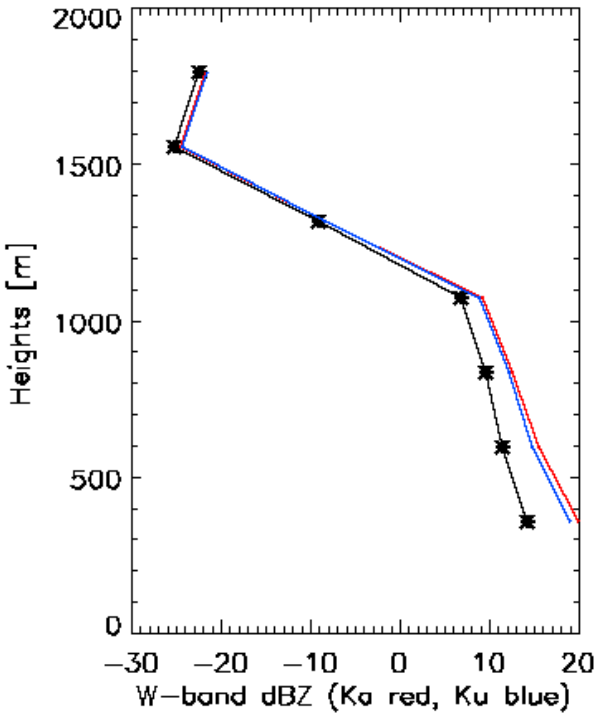
Retrieved Profiles: GPM Ka + Ku

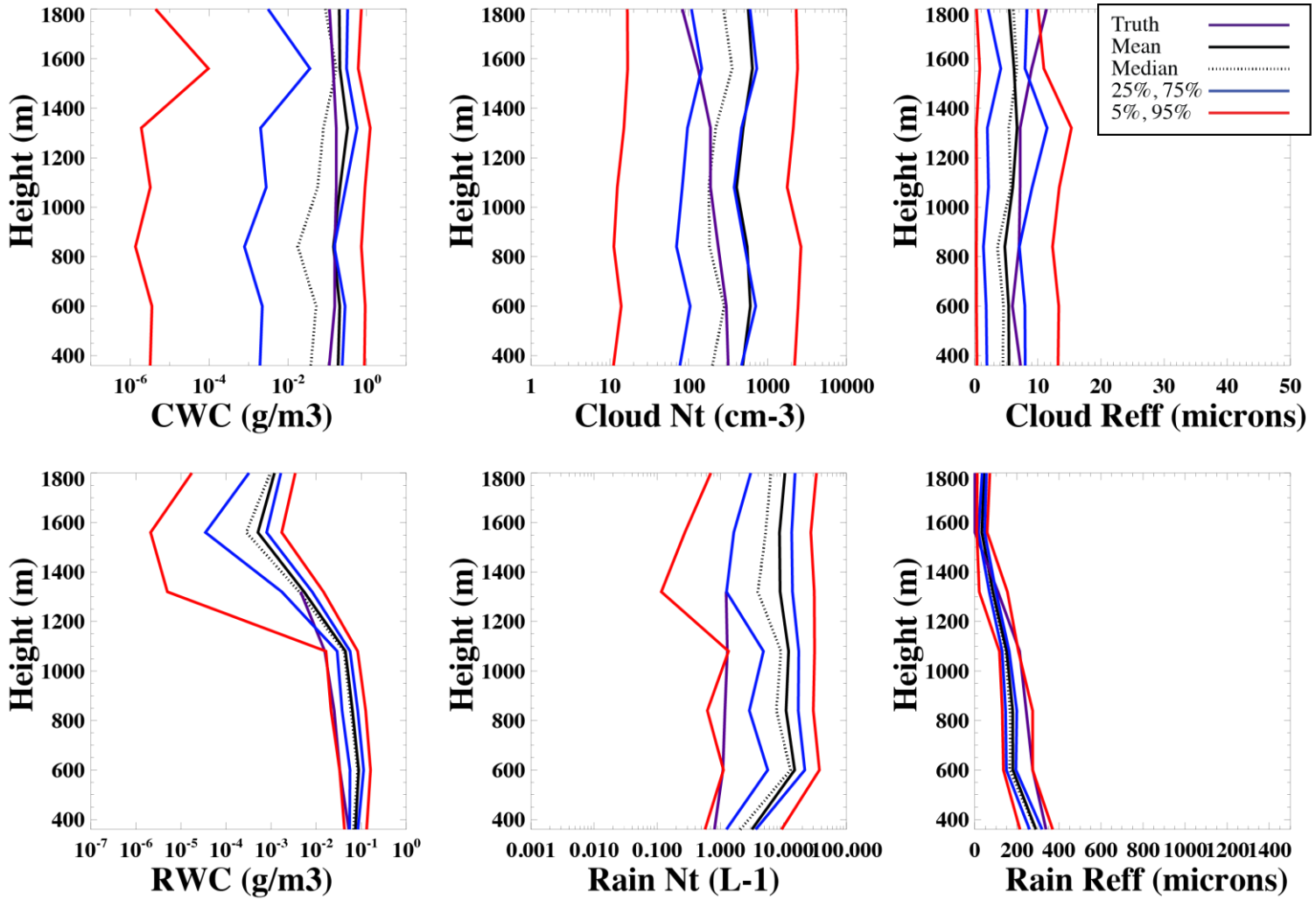




- Radar signal > noise floor below 800 m

Retrieved Profiles: CloudSat W + GPM Ka

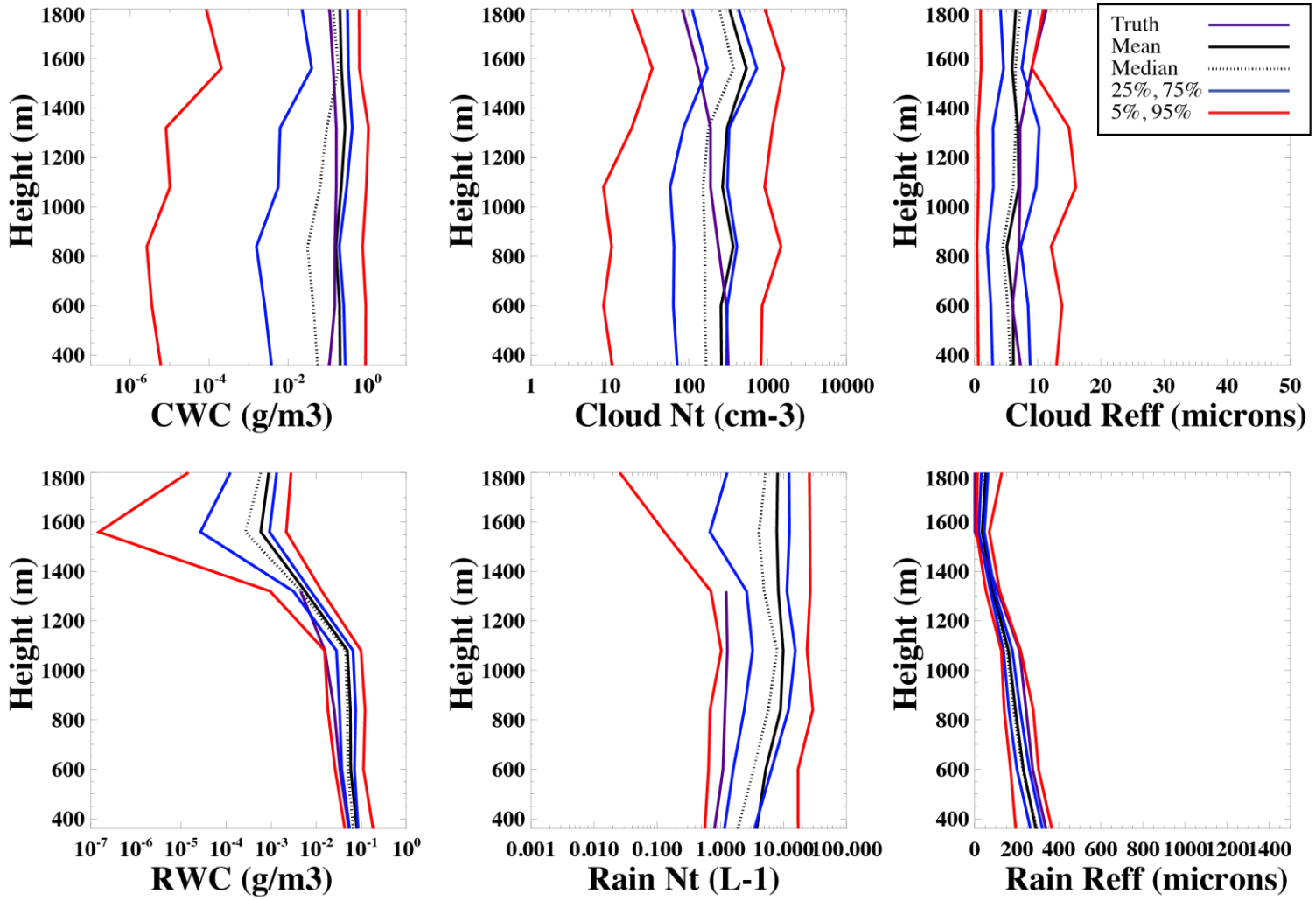




- Note that there is little to no precip mode above 1300 meters

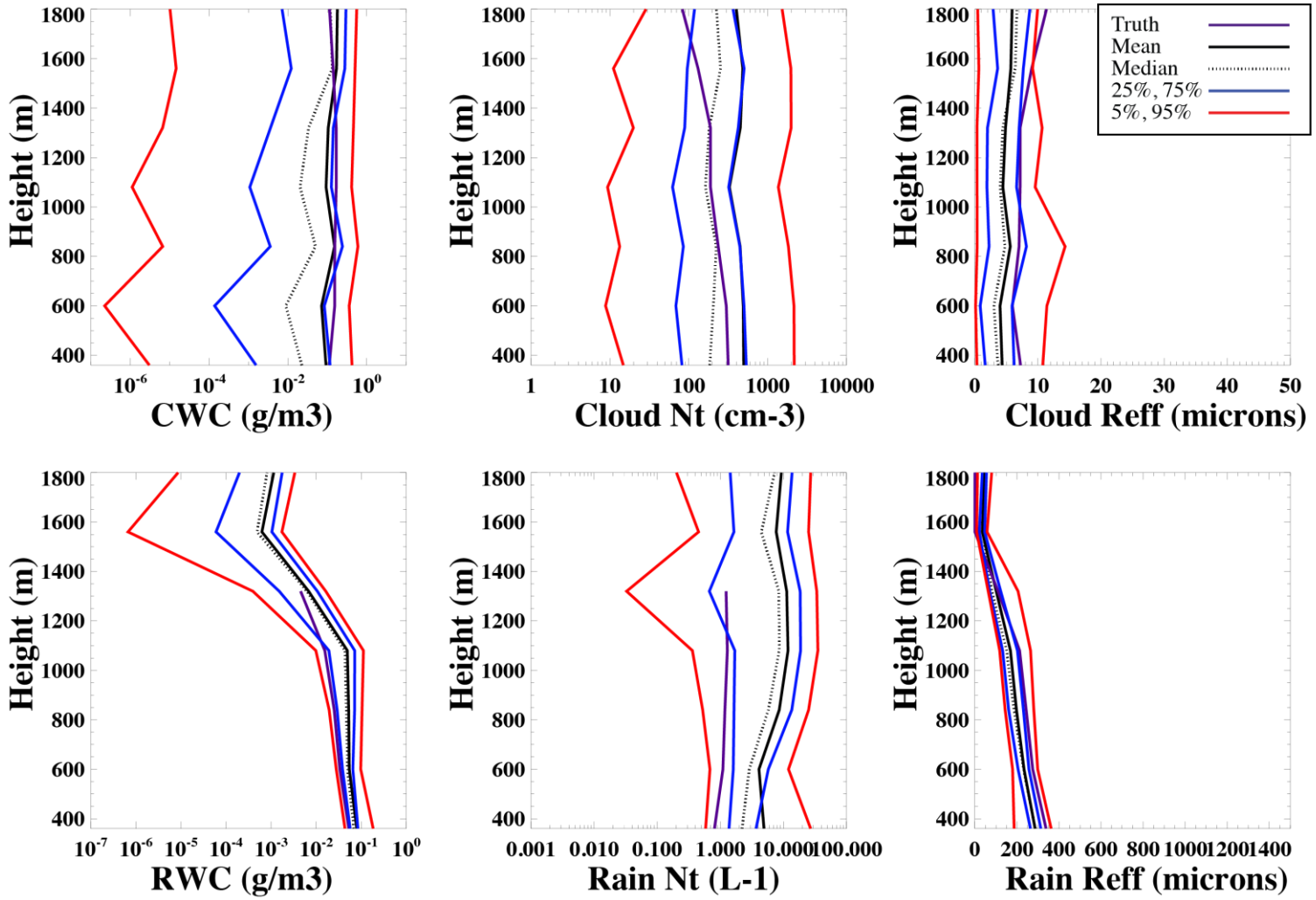
Retrieved Profiles: ACE W + Ka

- Assume more sensitive radar, consistent with ACE specifications
  W: -35 dBZ, Ka: -10 dBZ
- Subtle increase in accuracy of retrievals for all rain PSD properties, and for droplet water content and number



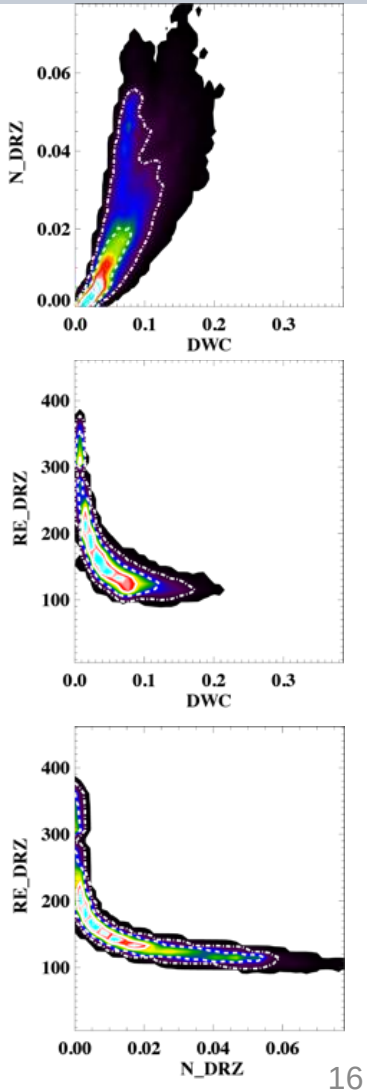
Retrieved Profiles: ACE W + Ka + Tb

- Add observations of radiometric brightness temperature at W and Ka bands
- Little additional information from Tb, but remember this cloud is very thin.



Bayesian Retrievals: Summary

- Remote sensing retrievals are perhaps best represented as a *distribution* of possible solutions
- PDF provides the most likely solution, and uncertainty
- A Bayesian MCMC methodology can be used for retrieval OSSEs: **quantitative evaluation of measurement strategies**
- For shallow liquid clouds, need sensitive W-band radar to obtain robust estimates of rain PSDs
- A relatively sensitive 2nd radar wavelength (Ka) provides a small improvement in the accuracy of droplet mode retrievals
- Future experiments:
  - Cloud top information provided by vis/near IR
  - Doppler velocity information
  - Extend analysis to other cases (OLYMPEX/RADEX)



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