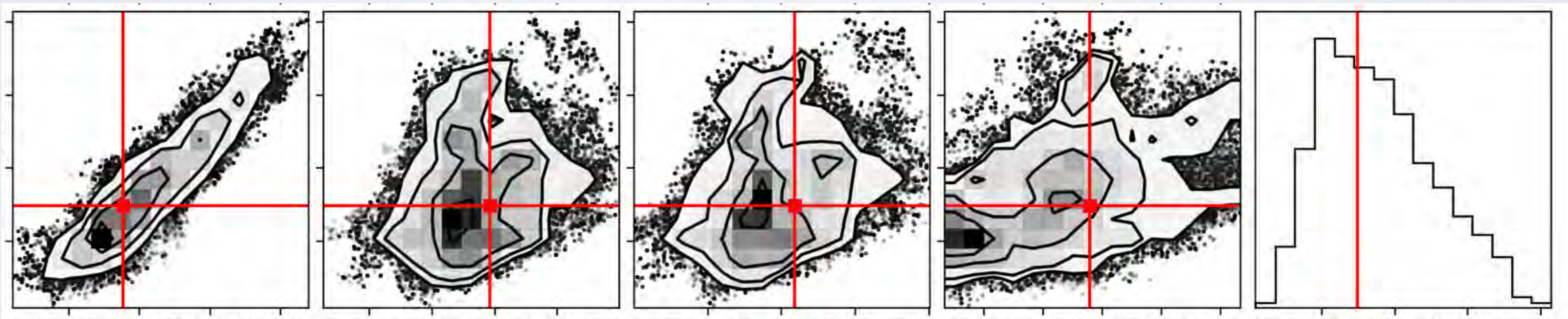
The Bayesian Observationally-constrained Statistical-physical Scheme (BOSS):

a novel microphysical parameterization framework that leverages uncertain observational information



Marcus van Lier-Walqui (Columbia U. & NASA/GISS)
Matthew Kumjian, Charlotte Martinkus (Penn State U.)
Hugh Morrison (NCAR)
Olivier Prat (NC State University & NOAA)

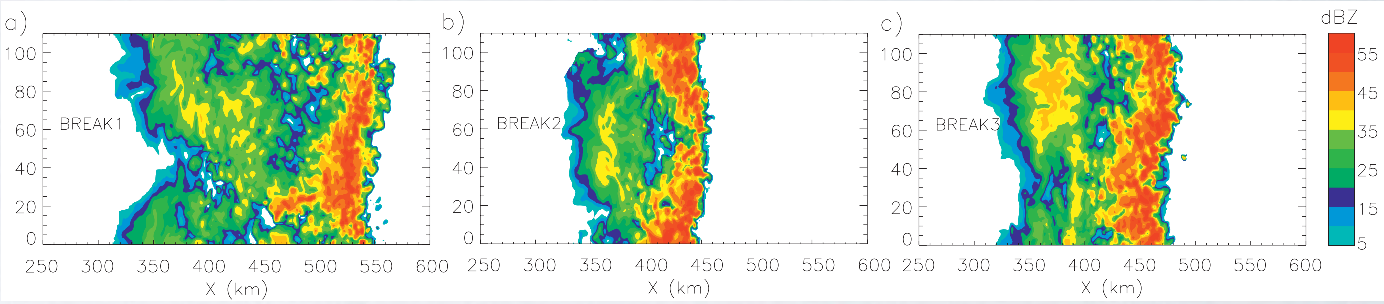
COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK

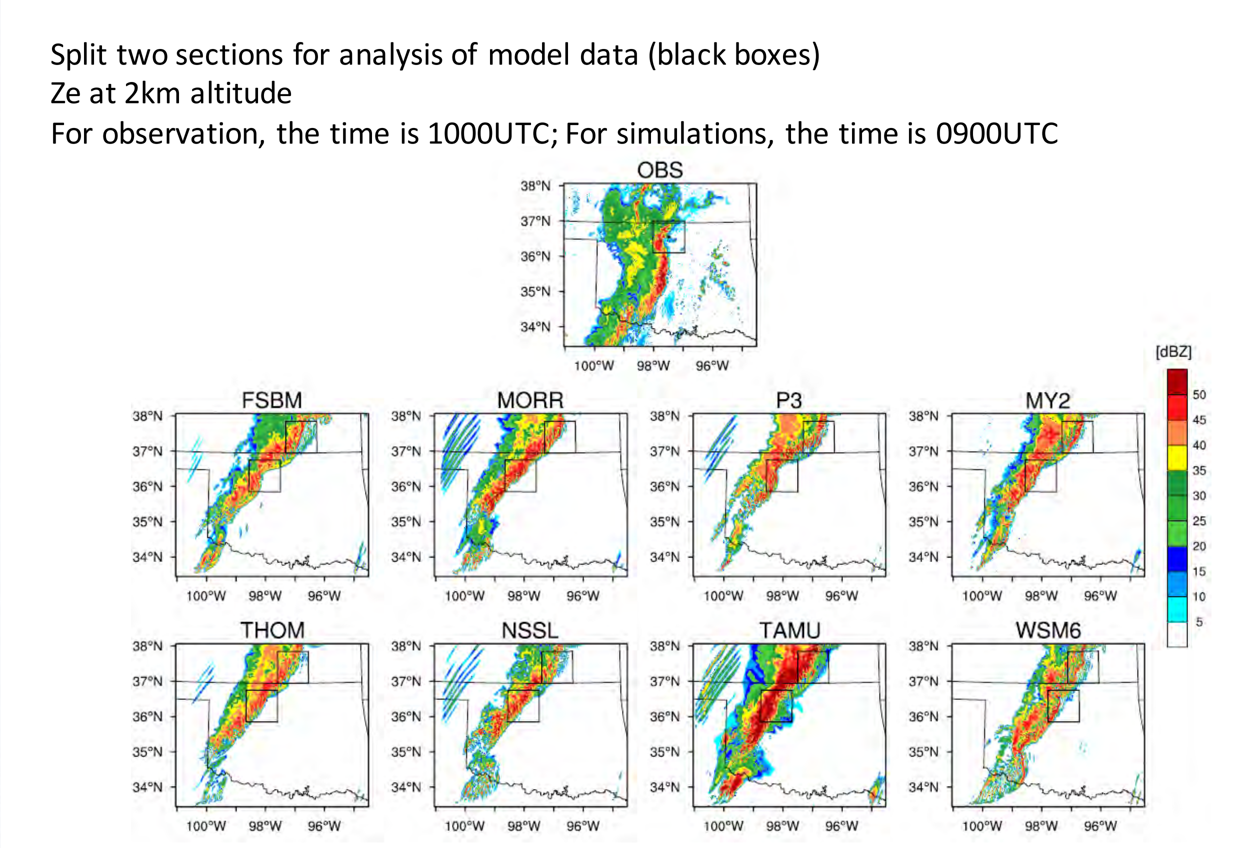
Big Trouble in Microphysics

- There are large gaps in our understanding and model representation of atmospheric processes
    - Cloud microphysics is a prime offender
- Result: our models have limited fidelity
- We have lots of observations, but do we use them well?
    - e.g. do we respect/understand their uncertainties?
    - e.g. do we fully utilize their information content?

Microphysics Uncertainty Results in Forecast Uncertainty

- Microphysics schemes have error/uncertainty/ approximations that result in:
    - Precipitation forecast error
    - For data assimilation: Poor ensemble spread
    - Limitations for use of models to understand microphysics





Split two sections for analysis of model data (black boxes)
Ze at 2km altitude
For observation, the time is 1000UTC; For simulations, the time is 0900UTC

(J. Fan)

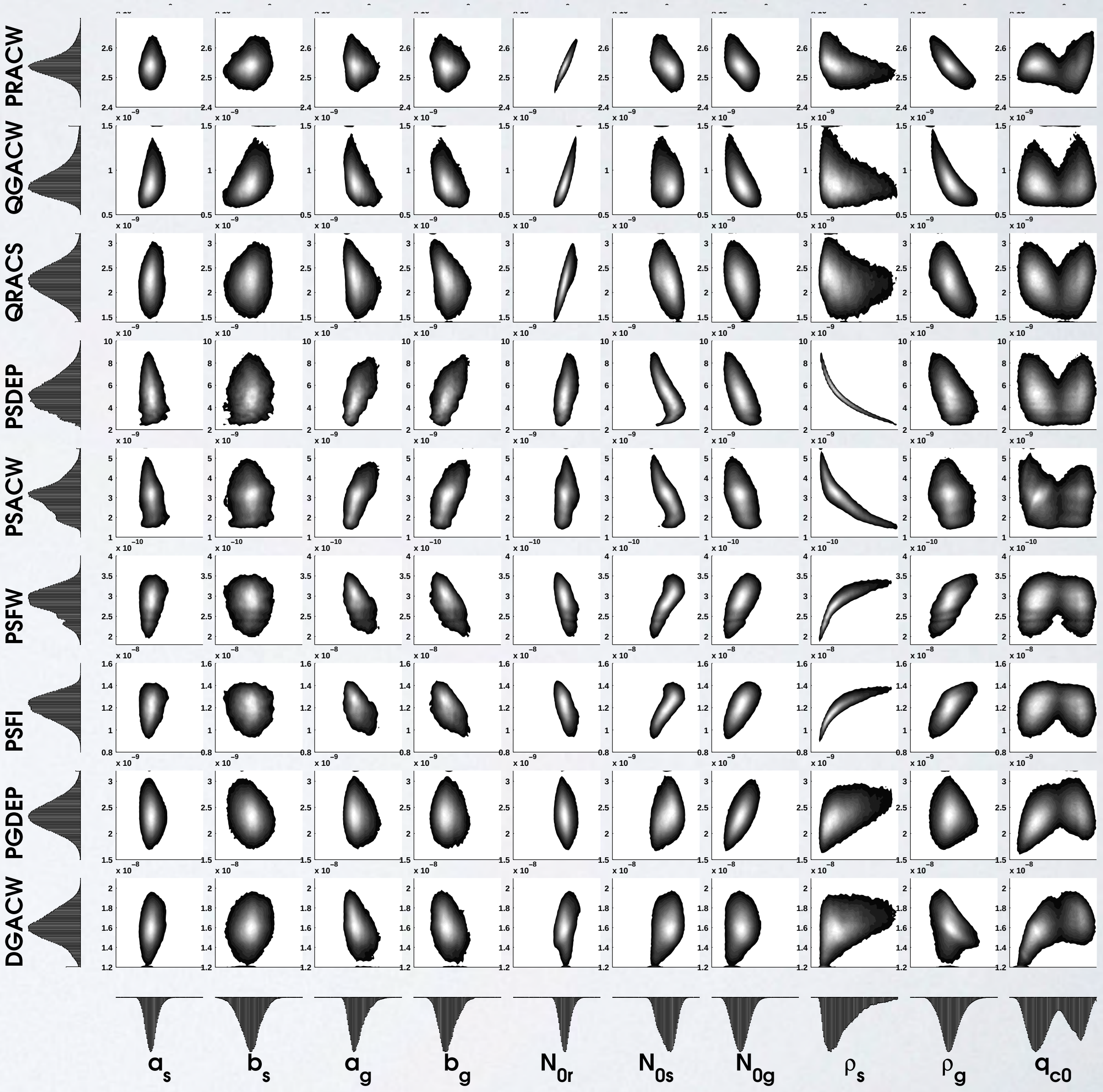
Tuning Knobs In Microphysics Schemes

Tuning Knobs In A "Black Box"

(Parametric Uncertainty)

Quantifying Microphysics Uncertainty can be done, but is not easy

- Posselt and Vukicevic 2010, van Lier-Walqui et al 2012, van Lier-Walqui et al 2014
- Estimate microphysics scheme parameter probability density with radar constraint
- Nonlinearities, non-Gaussian Probability Density Functions (PDFs) result in difficulties for parameter estimation



Parameter–Process Joint PDF – Convective (60 minutes)

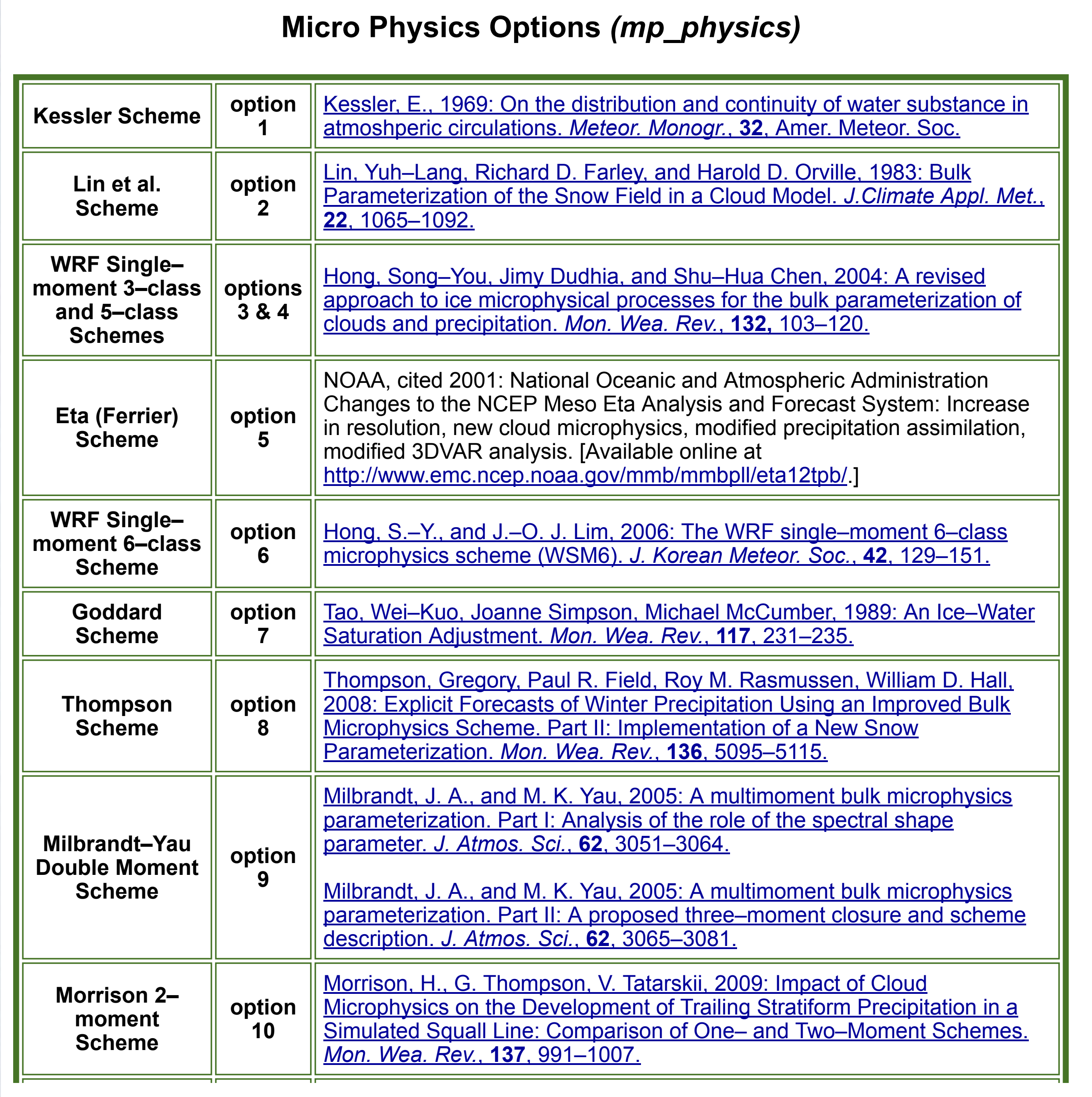
We're Still Just Turning Knobs

(Parametric Uncertainty)

And There Are Lots Of Black Boxes Out There!

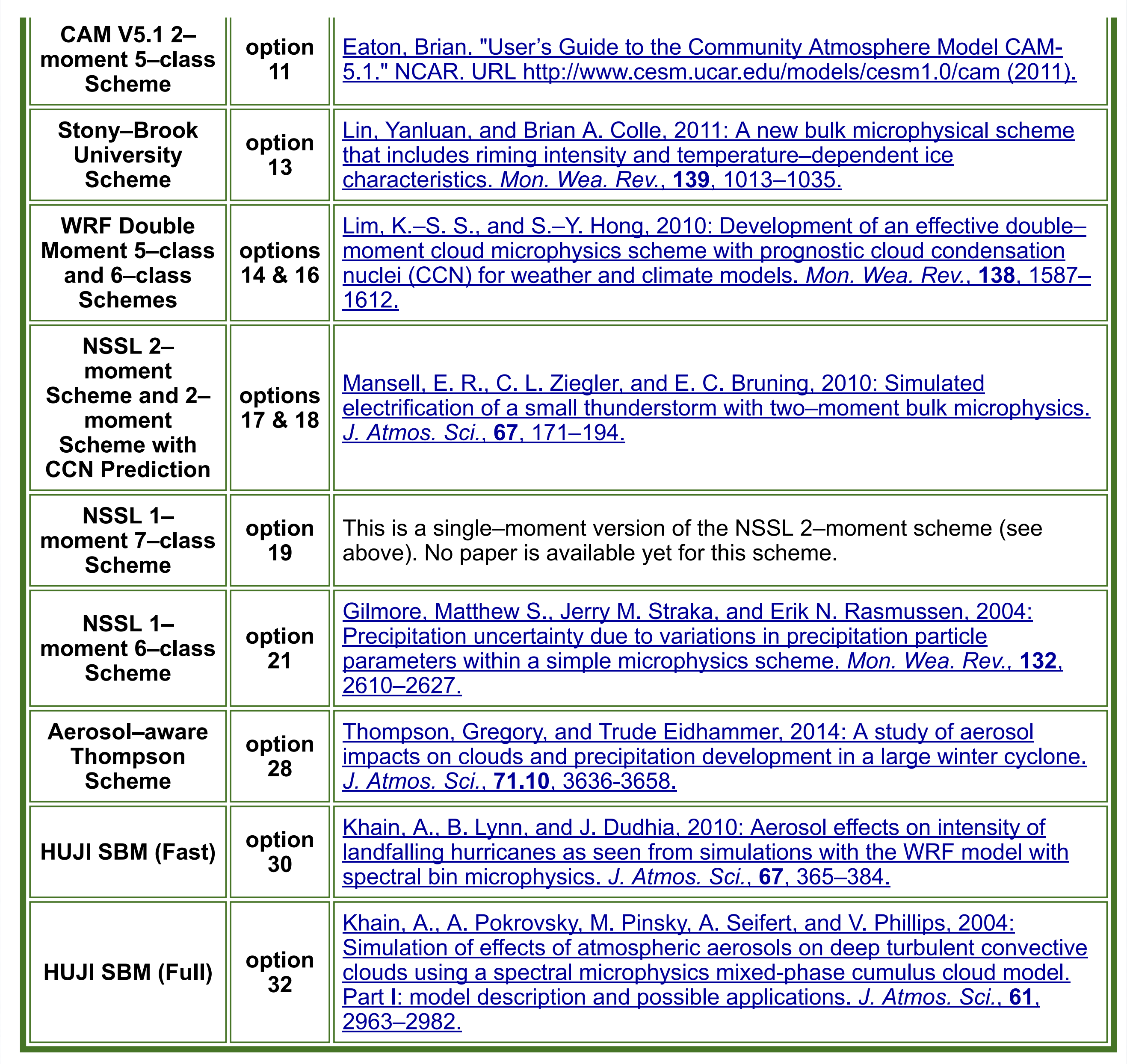
(Structural Uncertainty)

Many Microphysics options in WRF-ARW (~~18~~ 21)



Micro Physics Options *(mp_physics)*

Kessler Scheme	**option 1**	Kessler, E., 1969: On the distribution and continuity of water substance in atmoshperic circulations. *Meteor. Monogr.*, **32**, Amer. Meteor. Soc.
Lin et al. Scheme	**option 2**	Lin, Yuh–Lang, Richard D. Farley, and Harold D. Orville, 1983: Bulk Parameterization of the Snow Field in a Cloud Model. *J.Climate Appl. Met.*, **22**, 1065–1092.
WRF Single–moment 3–class and 5–class Schemes	**options 3 & 4**	Hong, Song–You, Jimy Dudhia, and Shu–Hua Chen, 2004: A revised approach to ice microphysical processes for the bulk parameterization of clouds and precipitation. *Mon. Wea. Rev.*, **132**, 103–120.
Eta (Ferrier) Scheme	**option 5**	NOAA, cited 2001: National Oceanic and Atmospheric Administration Changes to the NCEP Meso Eta Analysis and Forecast System: Increase in resolution, new cloud microphysics, modified precipitation assimilation, modified 3DVAR analysis. [Available online at http://www.emc.ncep.noaa.gov/mmb/mmbpll/eta12tpb/.]
WRF Single–moment 6–class Scheme	**option 6**	Hong, S.–Y., and J.–O. J. Lim, 2006: The WRF single–moment 6–class microphysics scheme (WSM6). *J. Korean Meteor. Soc.*, **42**, 129–151.
Goddard Scheme	**option 7**	Tao, Wei–Kuo, Joanne Simpson, Michael McCumber, 1989: An Ice–Water Saturation Adjustment. *Mon. Wea. Rev.*, **117**, 231–235.
Thompson Scheme	**option 8**	Thompson, Gregory, Paul R. Field, Roy M. Rasmussen, William D. Hall, 2008: Explicit Forecasts of Winter Precipitation Using an Improved Bulk Microphysics Scheme. Part II: Implementation of a New Snow Parameterization. *Mon. Wea. Rev.*, **136**, 5095–5115.
Milbrandt–Yau Double Moment Scheme	**option 9**	Milbrandt, J. A., and M. K. Yau, 2005: A multimoment bulk microphysics parameterization. Part I: Analysis of the role of the spectral shape parameter. *J. Atmos. Sci.*, **62**, 3051–3064. Milbrandt, J. A., and M. K. Yau, 2005: A multimoment bulk microphysics parameterization. Part II: A proposed three–moment closure and scheme description. *J. Atmos. Sci.*, **62**, 3065–3081.
Morrison 2–moment Scheme	**option 10**	Morrison, H., G. Thompson, V. Tatarskii, 2009: Impact of Cloud Microphysics on the Development of Trailing Stratiform Precipitation in a Simulated Squall Line: Comparison of One– and Two–Moment Schemes. *Mon. Wea. Rev.*, **137**, 991–1007.



CAM V5.1 2–moment 5–class Scheme	**option 11**	Eaton, Brian. "User's Guide to the Community Atmosphere Model CAM-5.1." NCAR. URL http://www.cesm.ucar.edu/models/cesm1.0/cam (2011).
Stony–Brook University Scheme	**option 13**	Lin, Yanluan, and Brian A. Colle, 2011: A new bulk microphysical scheme that includes riming intensity and temperature–dependent ice characteristics. *Mon. Wea. Rev.*, **139**, 1013–1035.
WRF Double Moment 5–class and 6–class Schemes	**options 14 & 16**	Lim, K.–S. S., and S.–Y. Hong, 2010: Development of an effective double–moment cloud microphysics scheme with prognostic cloud condensation nuclei (CCN) for weather and climate models. *Mon. Wea. Rev.*, **138**, 1587–1612.
NSSL 2–moment Scheme and 2–moment Scheme with CCN Prediction	**options 17 & 18**	Mansell, E. R., C. L. Ziegler, and E. C. Bruning, 2010: Simulated electrification of a small thunderstorm with two–moment bulk microphysics. *J. Atmos. Sci.*, **67**, 171–194.
NSSL 1–moment 7–class Scheme	**option 19**	This is a single–moment version of the NSSL 2–moment scheme (see above). No paper is available yet for this scheme.
NSSL 1–moment 6–class Scheme	**option 21**	Gilmore, Matthew S., Jerry M. Straka, and Erik N. Rasmussen, 2004: Precipitation uncertainty due to variations in precipitation particle parameters within a simple microphysics scheme. *Mon. Wea. Rev.*, **132**, 2610–2627.
Aerosol–aware Thompson Scheme	**option 28**	Thompson, Gregory, and Trude Eidhammer, 2014: A study of aerosol impacts on clouds and precipitation development in a large winter cyclone. *J. Atmos. Sci.*, **71.10**, 3636-3658.
HUJI SBM (Fast)	**option 30**	Khain, A., B. Lynn, and J. Dudhia, 2010: Aerosol effects on intensity of landfalling hurricanes as seen from simulations with the WRF model with spectral bin microphysics. *J. Atmos. Sci.*, **67**, 365–384.
HUJI SBM (Full)	**option 32**	Khain, A., A. Pokrovsky, M. Pinsky, A. Seifert, and V. Phillips, 2004: Simulation of effects of atmospheric aerosols on deep turbulent convective clouds using a spectral microphysics mixed-phase cumulus cloud model. Part I: model description and possible applications. *J. Atmos. Sci.*, **61**, 2963–2982.

Each scheme has Parametric Uncertainty,
Choice of scheme represents Structural Uncertainty

A challenge for constraining Microphysics Uncertainty

- How do we address parametric (best parameter values) AND structural (best choice of scheme structure) uncertainties?
  - Even if we perturb/estimate parameters in all available, existing schemes, how do we adequately weight individual schemes?
  - For ensemble prediction, how do we span the space between discrete choices of microphysics schemes?
- We need a new microphysics scheme framework to adequately address these questions

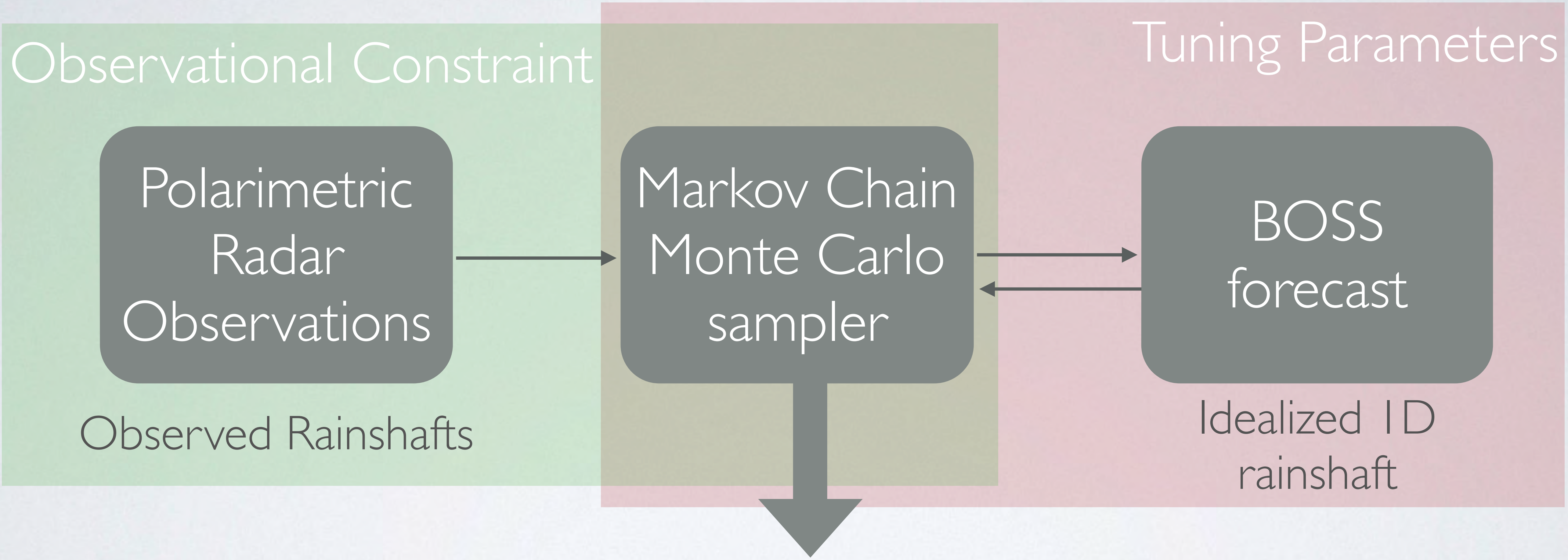
Microphysics scheme “wish-list”

- Flexible Drop Size Distribution (DSD) assumptions (no fixed functional form)
- Flexible process rate formulation (e.g. power series)
- Very few ad-hoc parameter choices and assumptions
- Structural complexity that can be added/subtracted as needed as required by comparison to observations

BOSS

- **B**ayesian (we treat uncertainties robustly)
- **O**bservationally-constrained (scheme is informed by comparison to observations)
- **S**tatistical-physical (we don’t just want a statistical scheme, but we will use statistics)
- **S**cheme (liquid-only at this point)

BOSS, Simplified



Observational Constraint

Tuning Parameters

Polarimetric Radar Observations

Markov Chain Monte Carlo sampler

BOSS forecast

Observed Rainshafts

Idealized 1D rainshaft

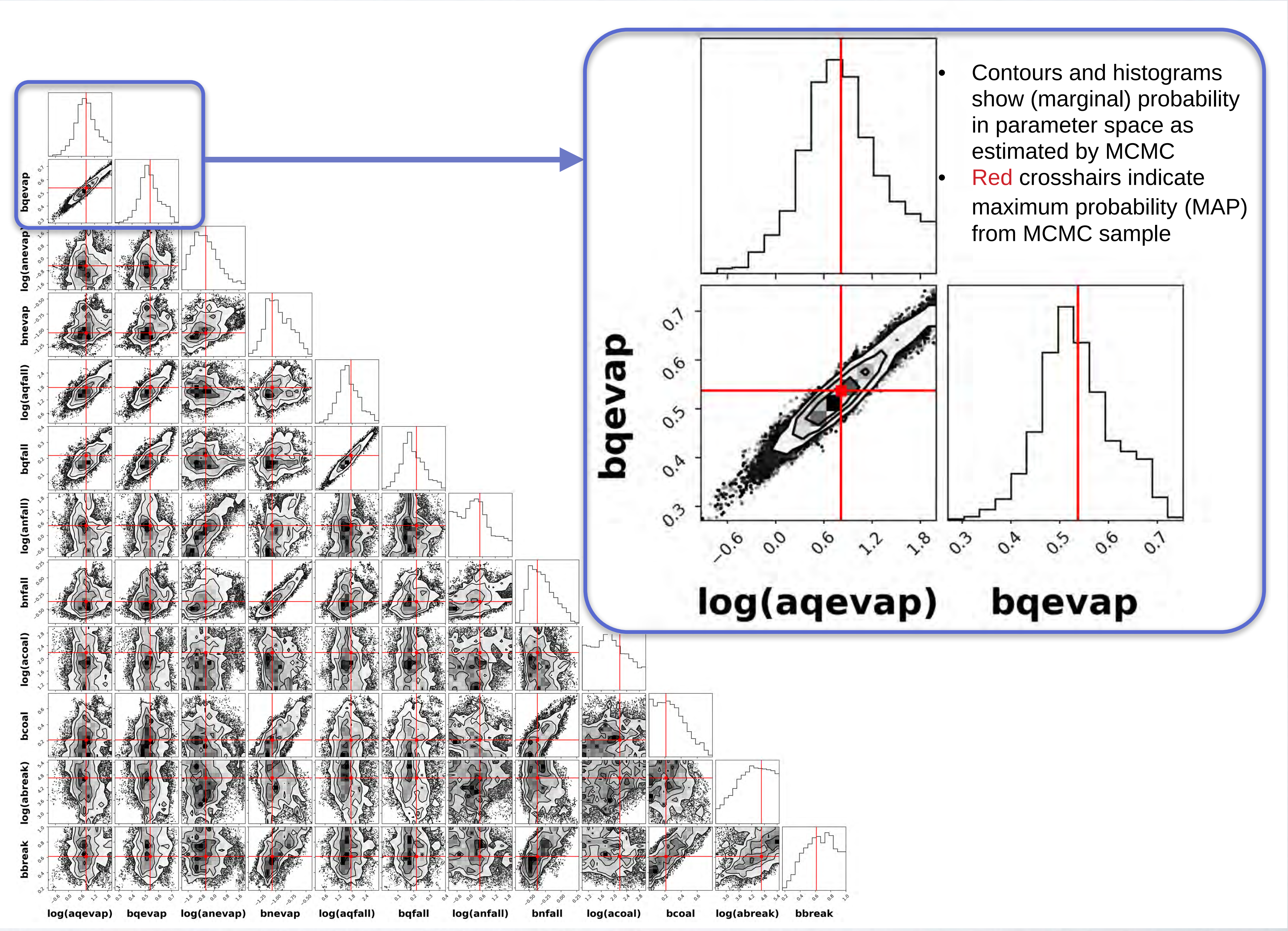
- PDF of parameter values
  - optimal parameter value
  - uncertainty in parameters
- Optimal complexity of BOSS

What do we get out of BOSS?

- Estimate of optimal parameter value *and* parameter uncertainty (probability density).
- Allows us to:
  - Forecast uncertainty due to microphysics uncertainty
  - Relationships/ sensitivity between observations, parameter values, and simulated microphysical processes (not shown)

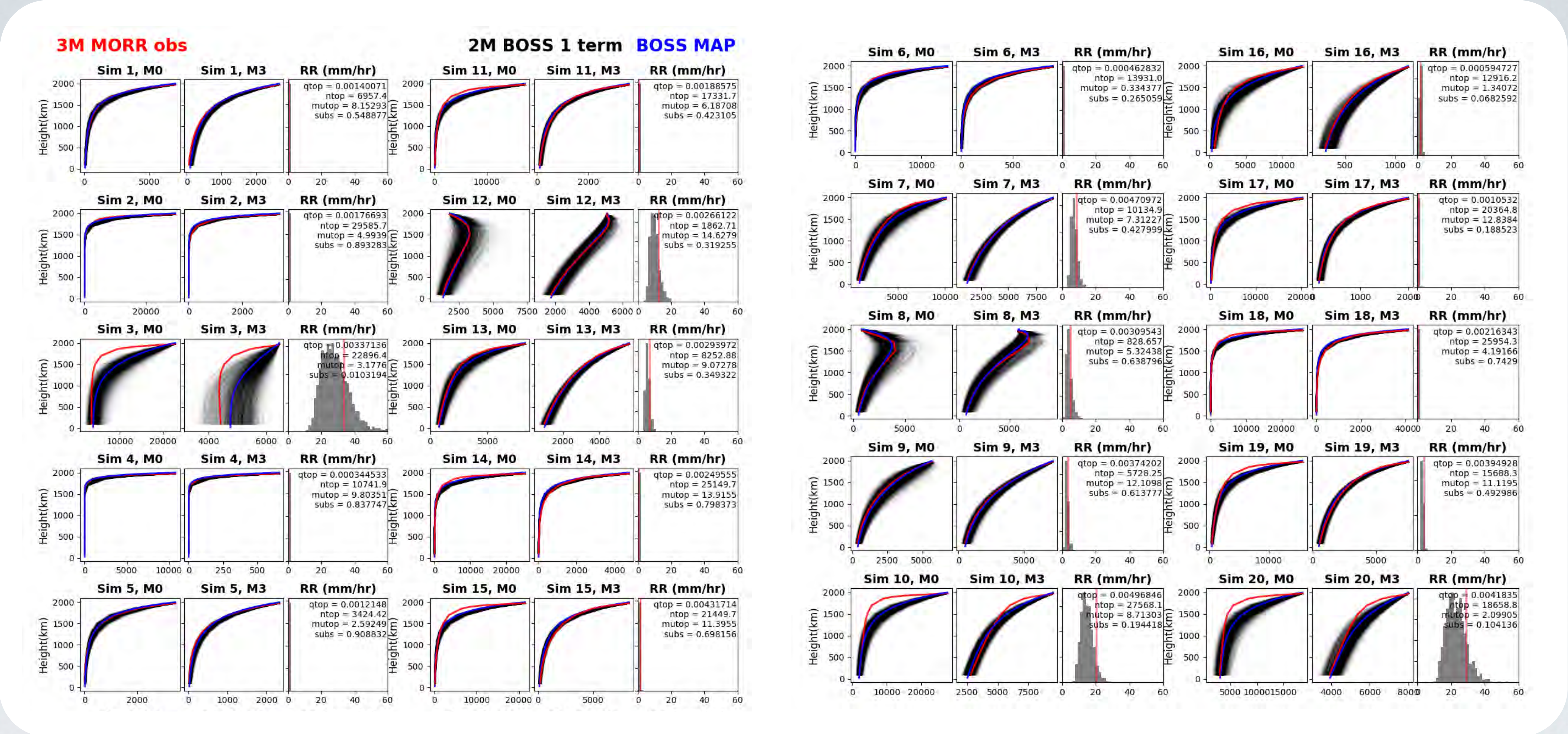
Parameter Probability Density Function (PDF)

2-moment (number, mass) BOSS, constrained by 3-moment MORR



- Contours and histograms show (marginal) probability in parameter space as estimated by MCMC
- Red crosshairs indicate maximum probability (MAP) from MCMC sample

Rainshaft Forecast Uncertainty
Constrained by 20 3-moment MORR simulations



- Generally good agreement between BOSS and MORR
- Evaporation-dominant cases are better constrained

- Uncertainty is also simulation-specific and represents where has BOSS is stronger/weaker

Forward Operator Challenges

- Typically, radar variables are calculated from a DSD, assuming some dependence on drop size, by integrating the DSD
- We have no DSD to integrate , only moments (any we choose, though!)
- $M_k \equiv \int_0^\infty D^k N(D) dD$

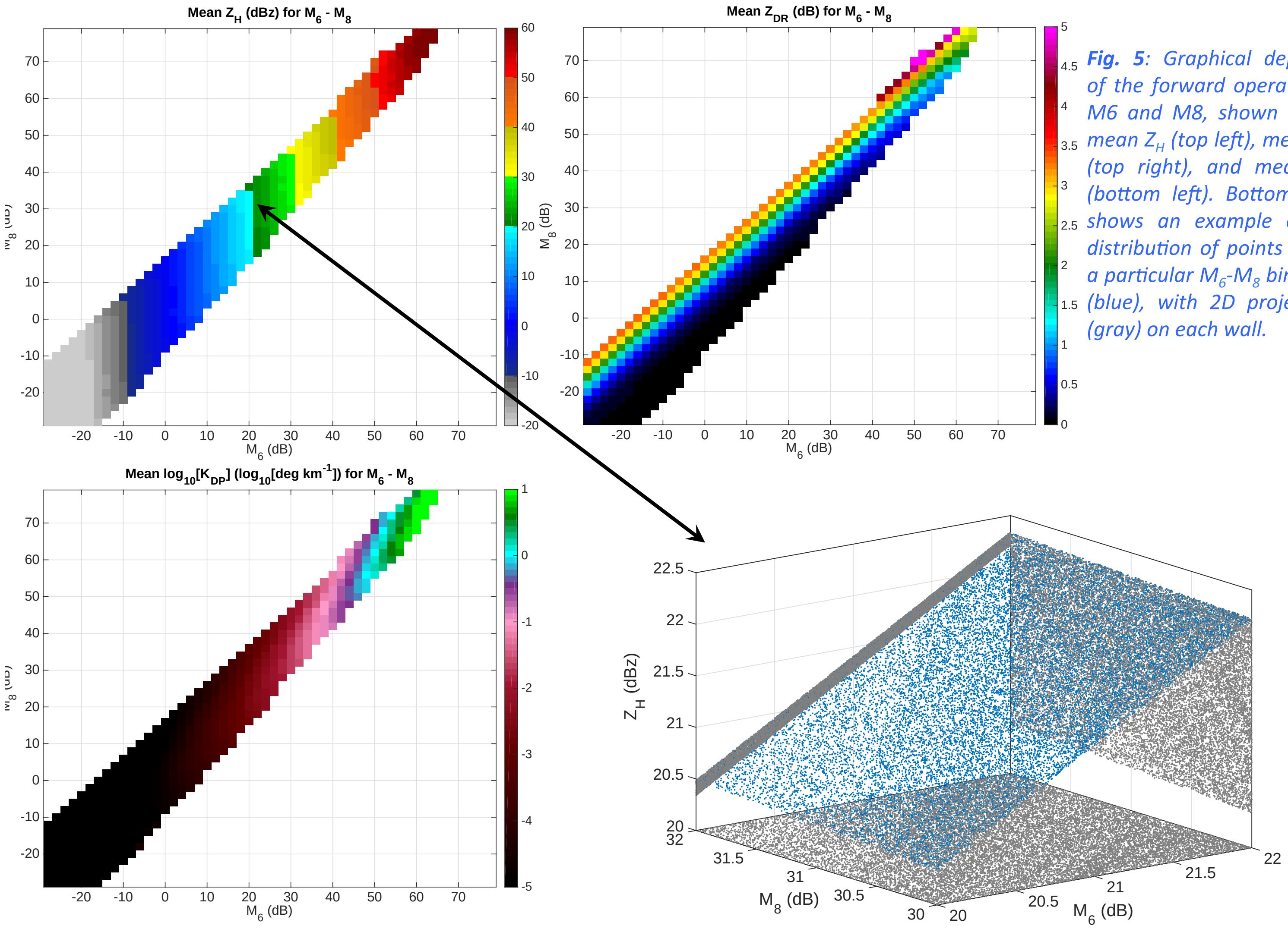


Fig. 5: *Graphical depiction of the forward operator for M6 and M8, shown as the mean Z_H (top left), mean Z_{DR} (top right), and mean K_{DP} (bottom left). Bottom right shows an example of the distribution of points within a particular M_6-M_8 bin in 3D (blue), with 2D projections (gray) on each wall.*

Kumjian et al Poster #120

- Mine bin DSDs (199,000,000+) to extract relationships between DSD moments and polarimetric observations
- Do the same for disdrometer data (21,600+ DSDs)
- Estimate forward simulator uncertainty based on spread in radar variables for a given prognostic moment combination

CONCLUSIONS

- We have created a new microphysics scheme that:
  - eschews assumptions about DSD and functional form of process rates
  - Allows for constraint and estimation of both parametric and structural uncertainty using observations

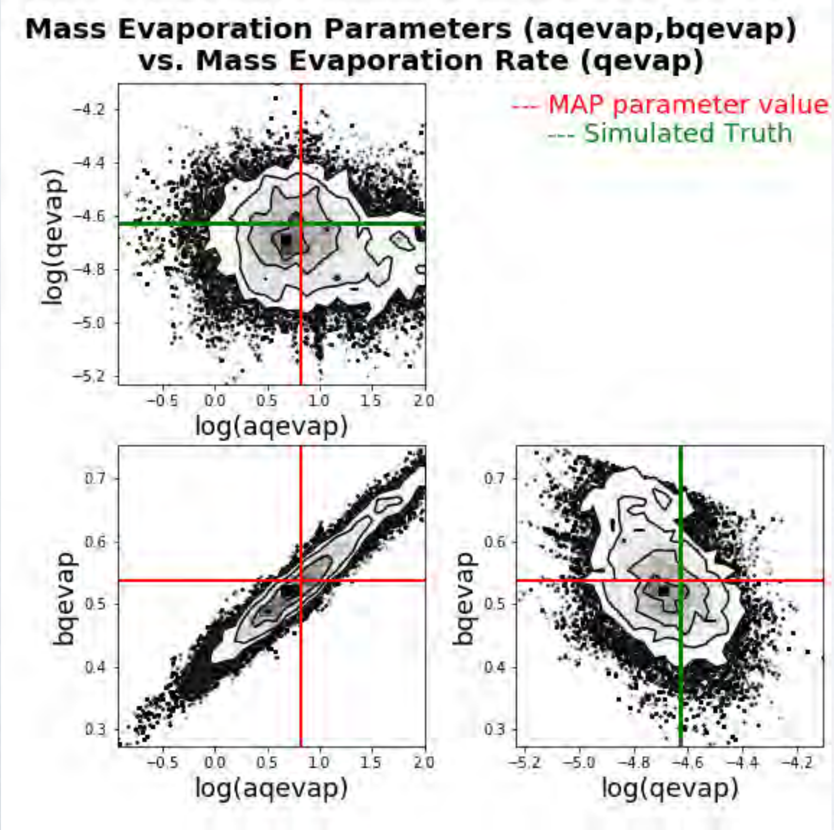
- Ongoing challenges:
  - Develop radar forward operator (poster #120)
  - Assemble appropriate observations
  - Develop MCMC sampler to automatically choose number of power-series terms

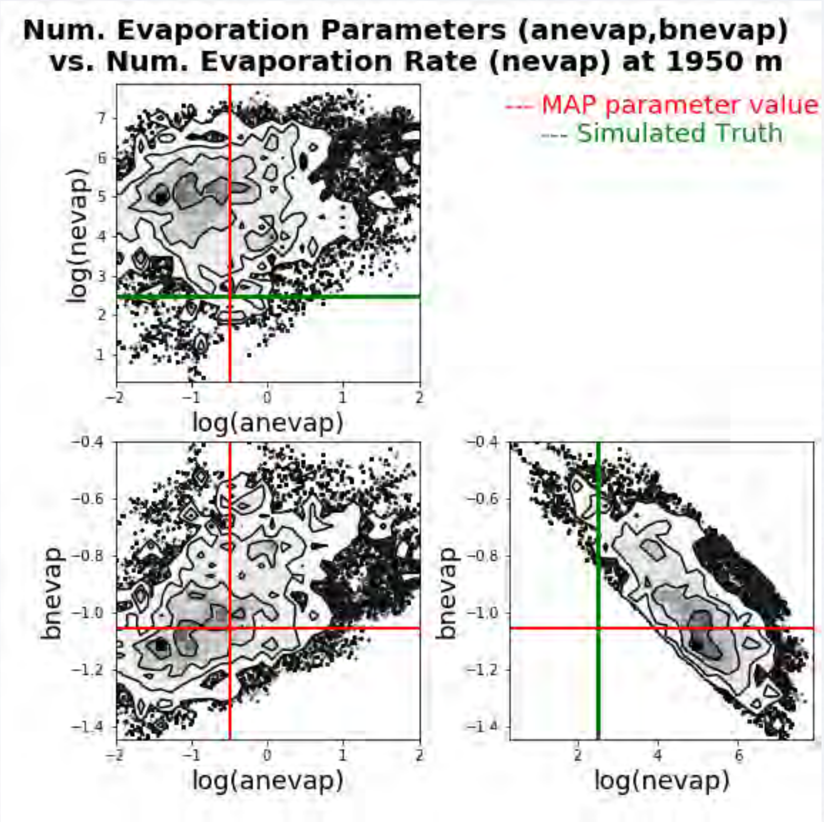
Come visit our posters! — #119 & #120

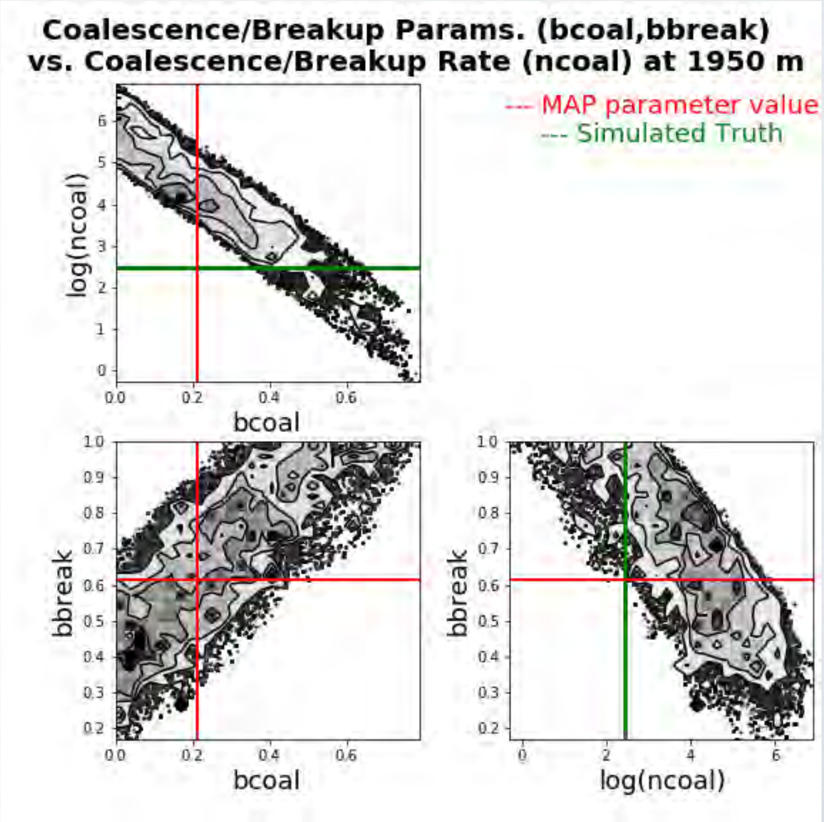
Process PDFs

- Joint plots show relationships between parameter perturbation and process response

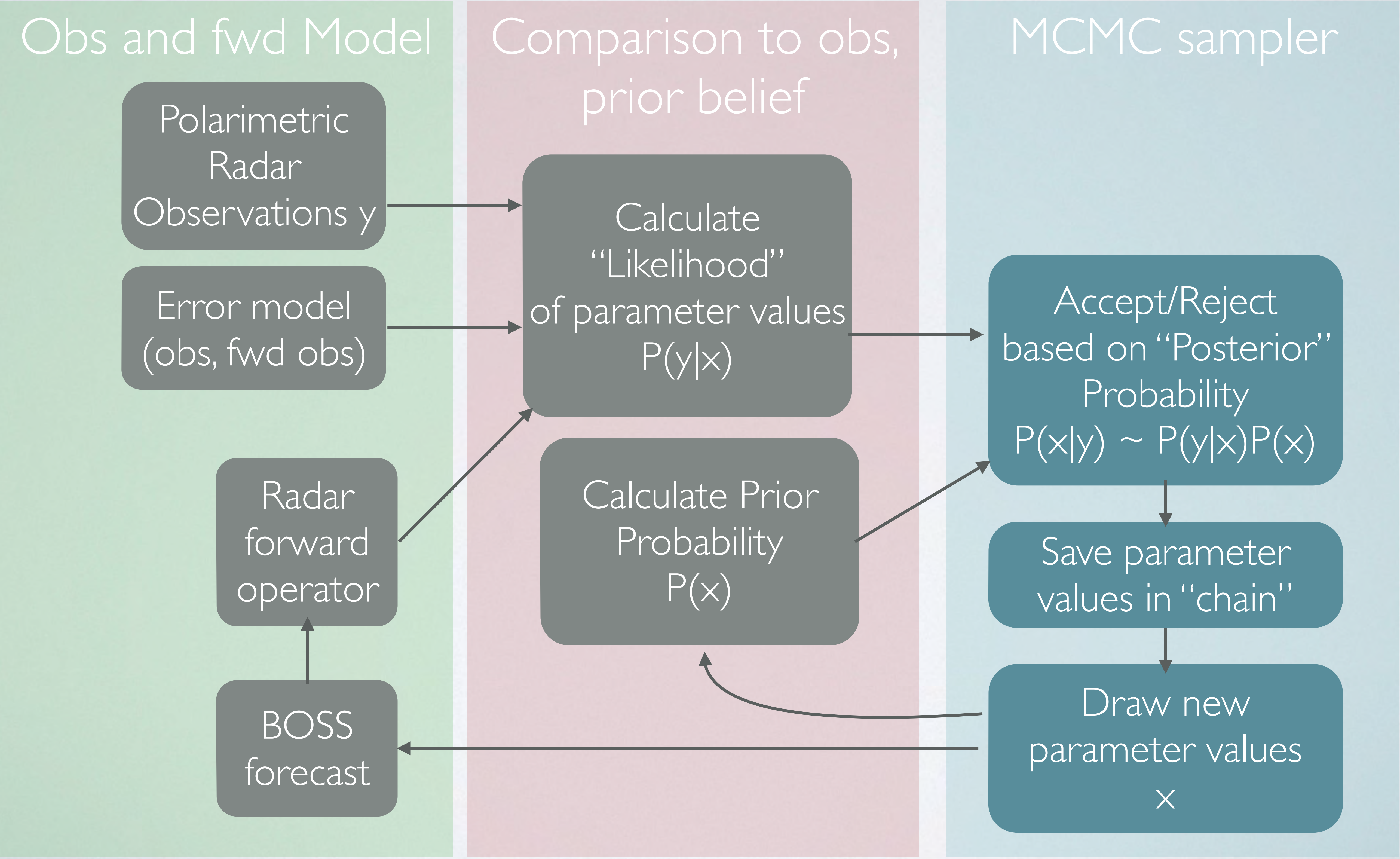
- Mass evaporation is well constrained
- Processes that affect number are poorly constrained (number evaporation, collision-coalescence, breakup


Mass Evaporation Parameters (aqevap,bqevap) vs. Mass Evaporation Rate (qevap)


Num. Evaporation Parameters (anevap,bnevap) vs. Num. Evaporation Rate (nevap) at 1950 m


Coalescence/Breakup Params. (bcoal,bbreak) vs. Coalescence/Breakup Rate (ncoal) at 1950 m

BOSS, More Complicated



Obs and fwd Model

Polarimetric Radar Observations y

Error model (obs, fwd obs)

Radar forward operator

BOSS forecast

Comparison to obs, prior belief

Calculate "Likelihood" of parameter values P(y|x)

Calculate Prior Probability P(x)

MCMC sampler

Accept/Reject based on "Posterior" Probability P(x|y) ~ P(y|x)P(x)

Save parameter values in "chain"

Draw new parameter values x