Using radar reflectivity to quantify microphysical parameterization uncertainty

Marcus van Lier-Walqui

Rosenstiel School of Marine and Atmospheric Science
University of Miami

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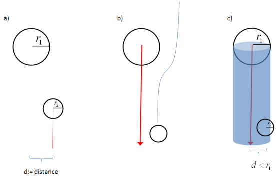
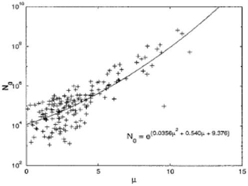
Outline

NWP Microphysical Parameterization

Why do we need it?

- Precipitation processes occur on a microscopic scale.
- Hydrometeors come in all sizes, shapes, habits.
- Must parameterize to reduce cost.
  - Approximate particle size distribution as Gamma or . . .
  - Treat one moment of PSD as prognostic variable.





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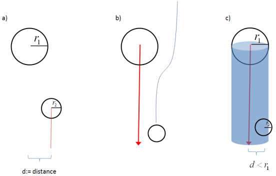

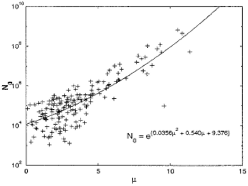

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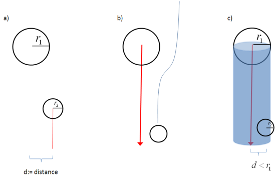

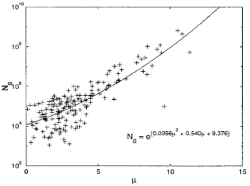

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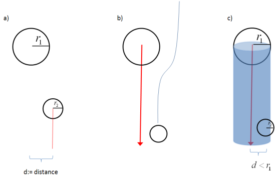

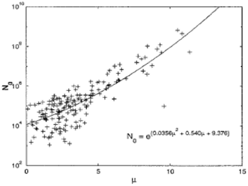

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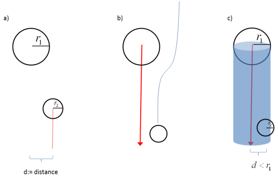

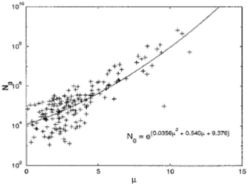

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- Sensitivity analysis
  - Single model, parameter perturbation [Thompson et al., 2004]
  - Multi-model [Stensrud et al., 2000]
  - Regional sensitivity analysis [Liu et al., 2004]
- Data assimilation techniques
  - EnKF [Tong and Xue, 2008]
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Markov chain Monte-Carlo (MCMC)

Basic Metropolis-Hastings sampling:

- Take first sample (prior), calculate likelihood
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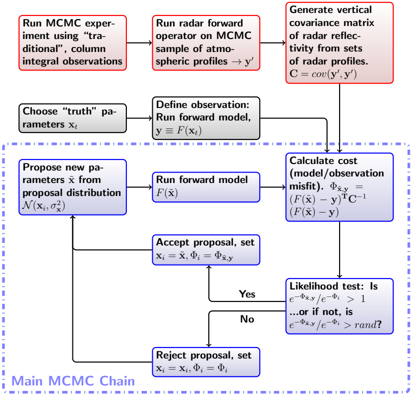

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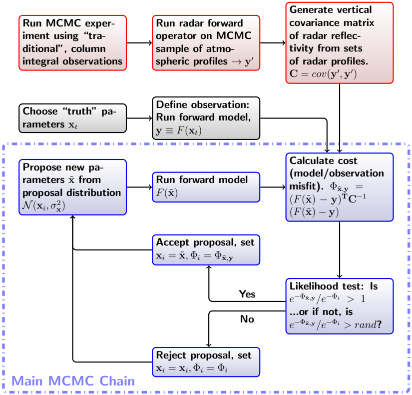

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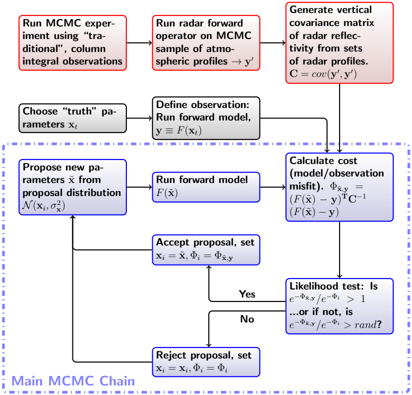

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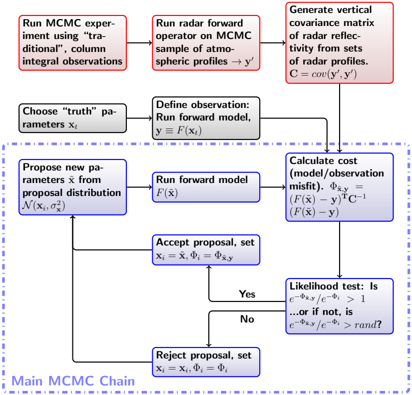

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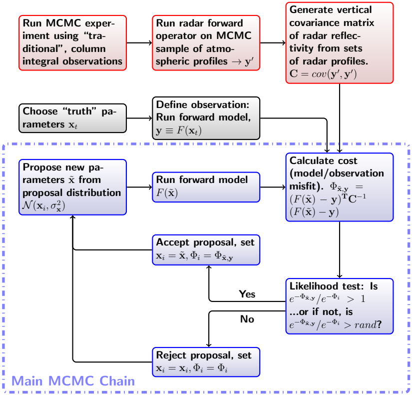

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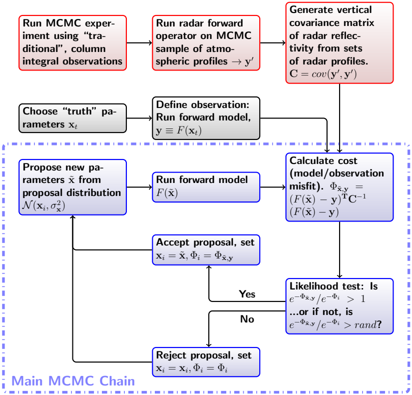

Research Goals:

- Estimate uncertainty in microphysical parameterization *constrained by* radar reflectivity observations.
- Use probabilistic inverse modeling to study the multivariate, non-linear relationships between parameters, observations and individual microphysical processes.
- Provide a theoretical foundation for stochastic microphysical parameterization.

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What is the likelihood?

$$Posterior = \frac{Prior \cdot Likelihood}{Normalizer} \quad (1)$$

Assuming Gaussian error in our observations, the likelihood is:

$$L(\mathbf{x}) = e^{-\Phi_{\mathbf{xy}}}, \quad (2)$$

$$\Phi_{\mathbf{xy}} = (f(\mathbf{x}) - \mathbf{y})^{\mathbf{T}}\mathbf{C}^{-1}(f(\mathbf{x}) - \mathbf{y}) \quad (3)$$

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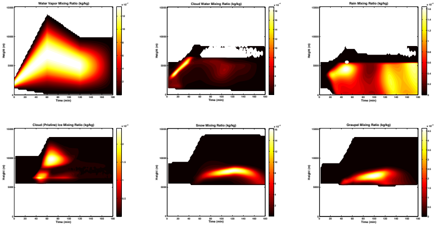
- 1D Column model
- Prescribed forcing to simulate behavior of mid-latitude squall line
- Full bulk 1-moment microphysics parameterization [Lin et al., 1983]



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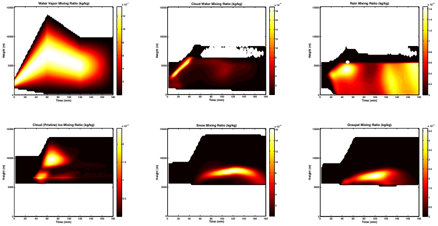

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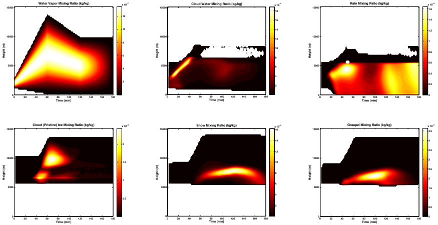
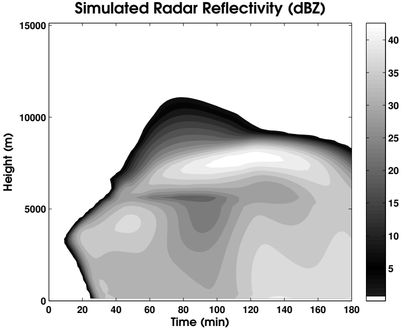


Radar Reflectivity Simulator

- Quickbeam radar simulator [Haynes et al., 2007]
- Assumes Mie scattering
- $3GHz$ radar frequency
- Attenuation and bright-band not simulated
- Observations taken at 60m (convective) and 120m (stratiform)



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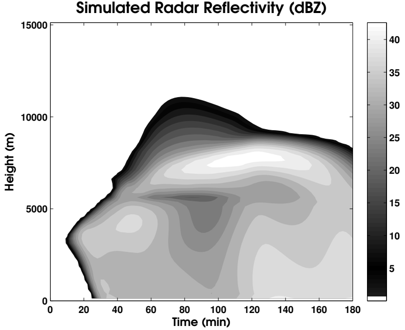

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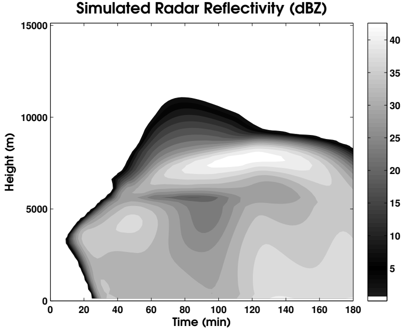

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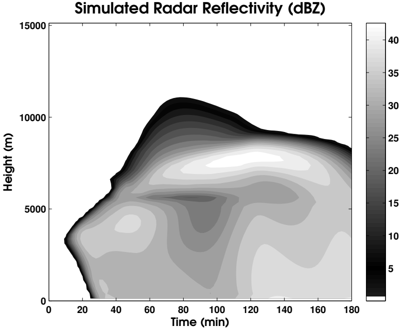

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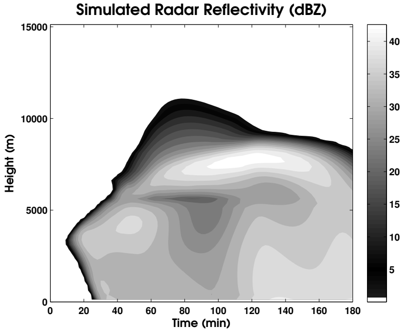

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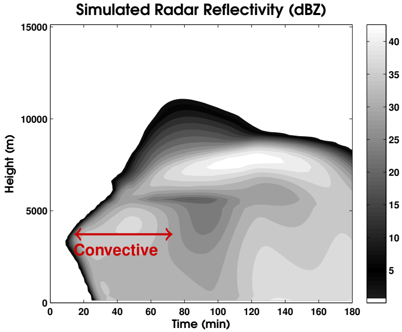

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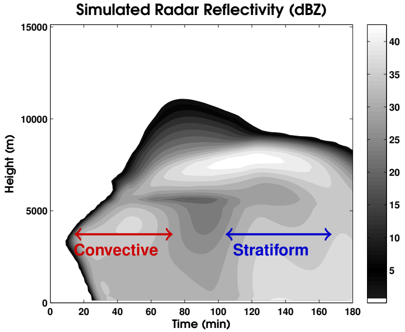

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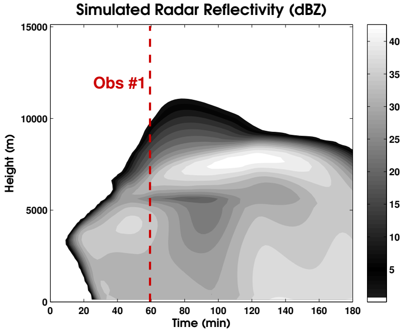

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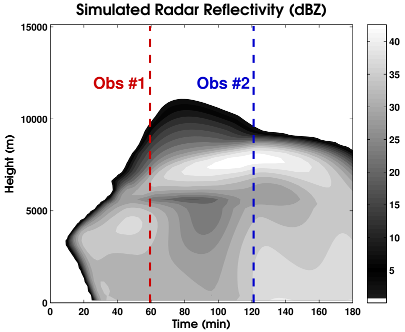


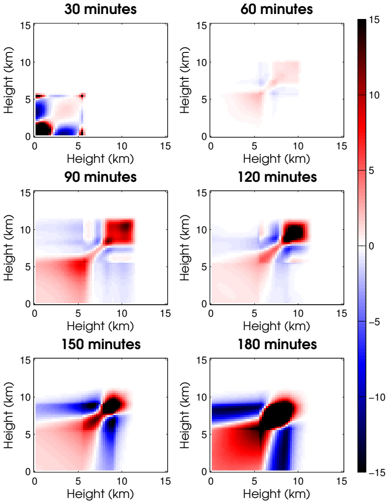
NB: Radar obs. are vertically resolved (at all 62 model levels)

Microphysical Parameters

Parameter description	Abbreviation	Units	Truth	Min	Max
Snow fall speed coefficient	a_s	cm$^{1-b_s}$	200.0	50.0	1000.0
Snow fall speed exponent	b_s	none	0.3	0.1	1.0
Graupel fall speed coefficient	a_g	cm$^{1-b_g}$	400.0	50.0	1200.0
Graupel fall speed exponent	b_g	none	0.4	0.1	0.9
Intercept parameter, rain particle size distribution	N_{0r}	cm^{-4}	0.5	0.0	5.0
Intercept parameter, snow particle size distribution	N_{0s}	cm^{-4}	0.5	0.0	5.0
Intercept parameter, graupel particle size distribution	N_{0g}	cm^{-4}	0.5	0.0	5.0
Snow particle density	ρ_s	g cm^{-3}	0.2	0.1	1.0
Graupel particle density	ρ_g	g cm^{-3}	0.4	0.1	1.0
Threshold cloud mixing ratio for autoconversion to rain	q_{c0}	g kg^{-1}	1.0	0.1	3.0

Radar Error Estimation

- Assume: radar uncertainty is correlated in the vertical
- Use "best estimate" of radar uncertainty
- An ensemble representing uncertainty in atmospheric state
- Ensemble generated via MCMC with column-integral obs [Posselt and Vukicevic, 2010]



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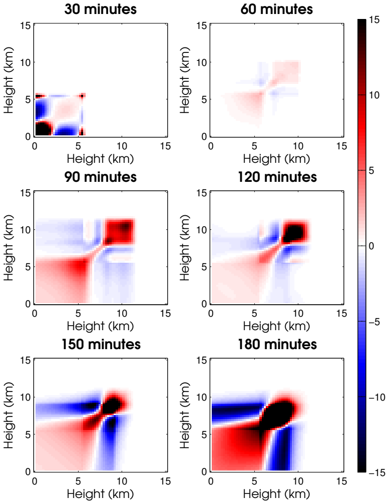

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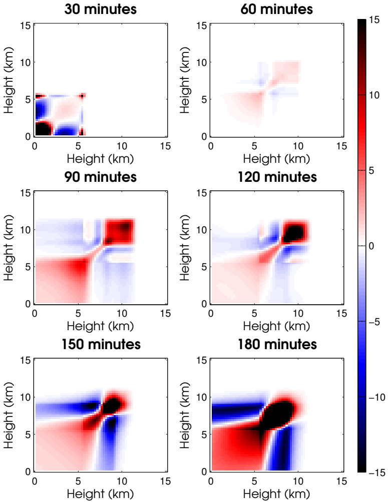

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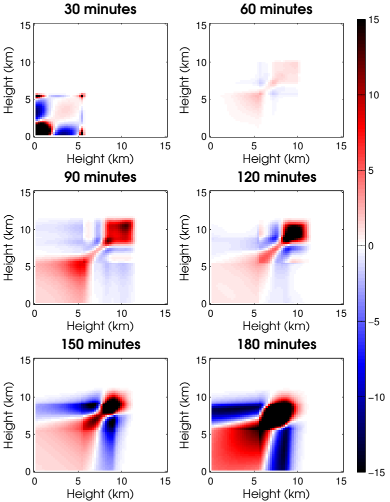

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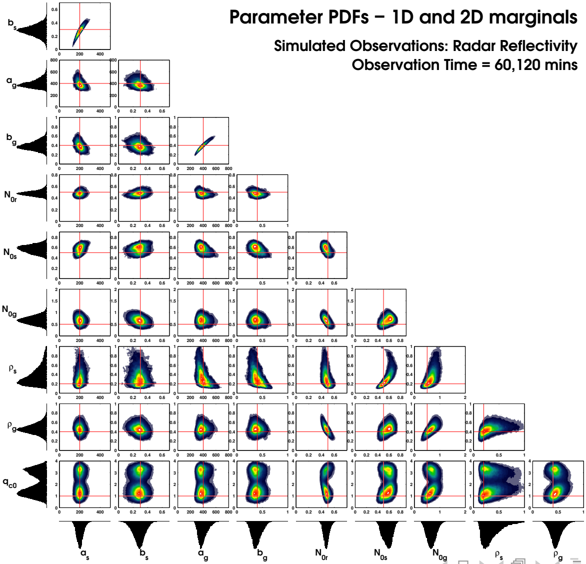

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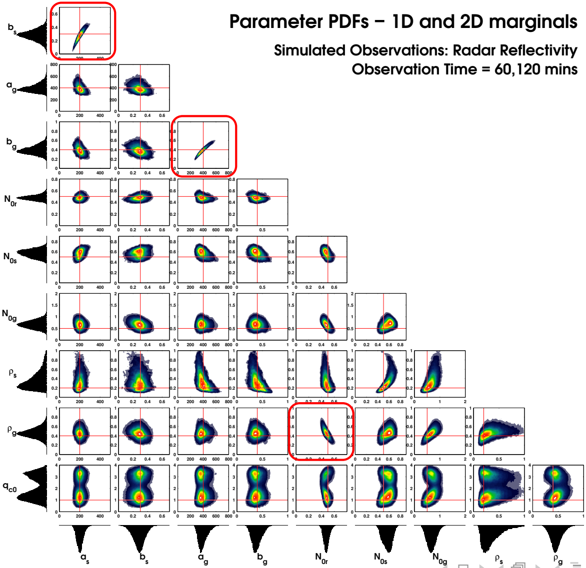

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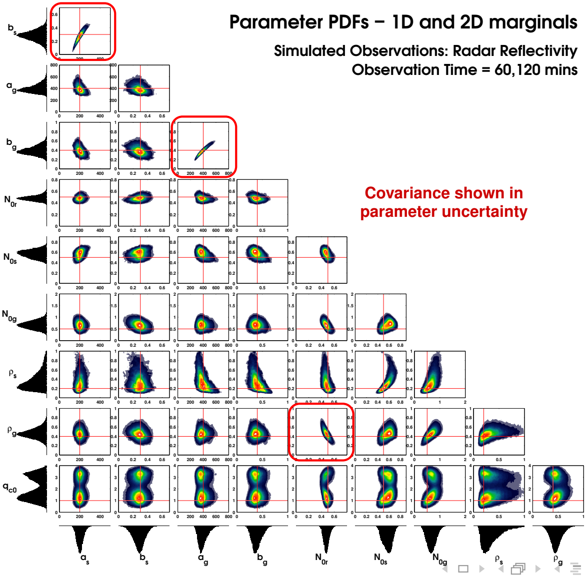

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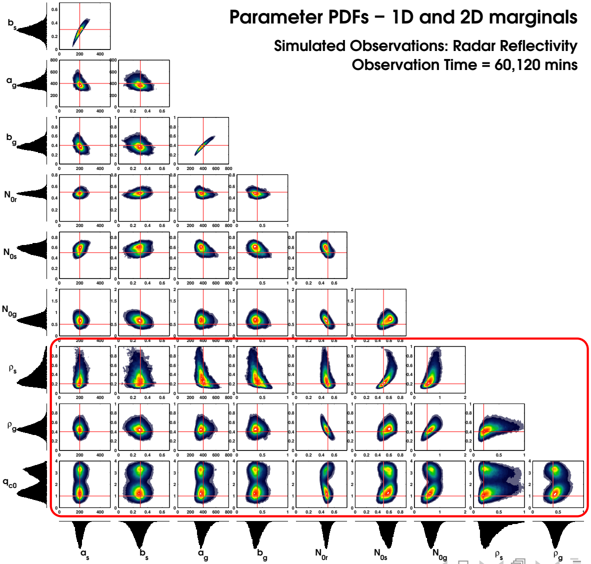

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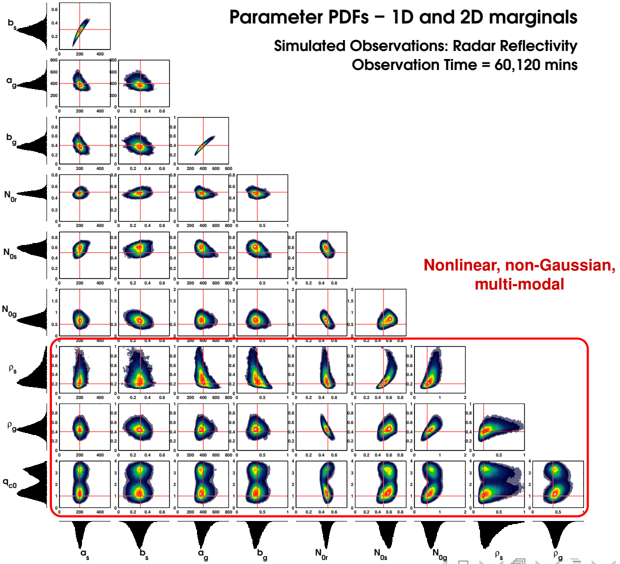

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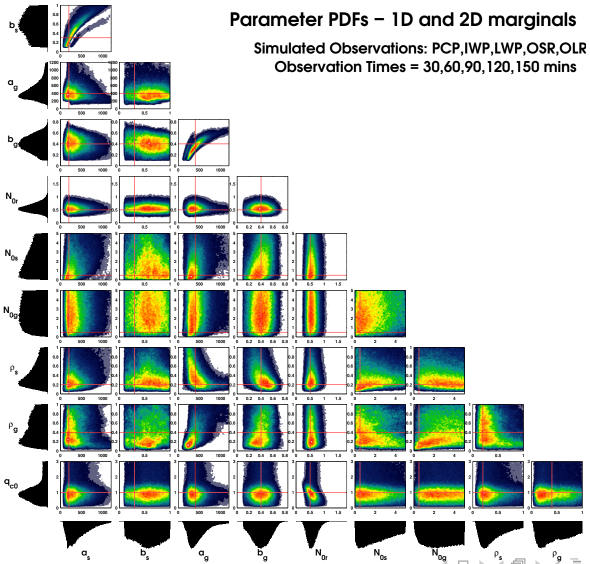

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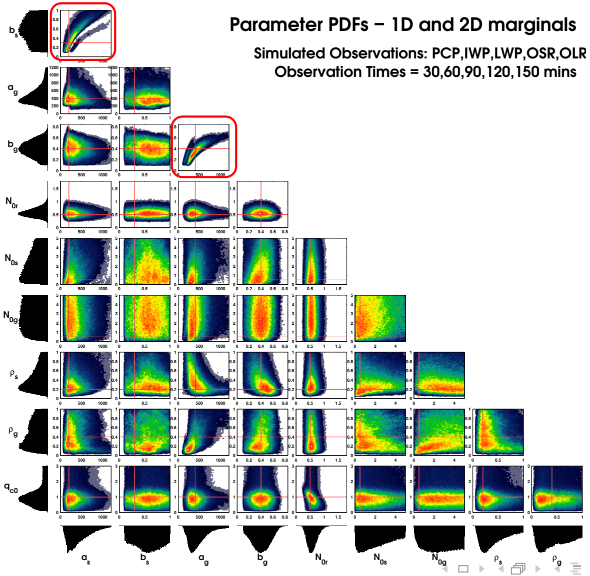

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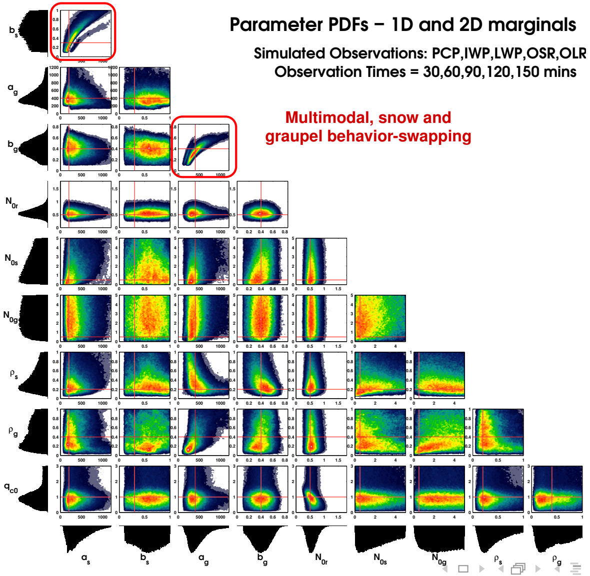
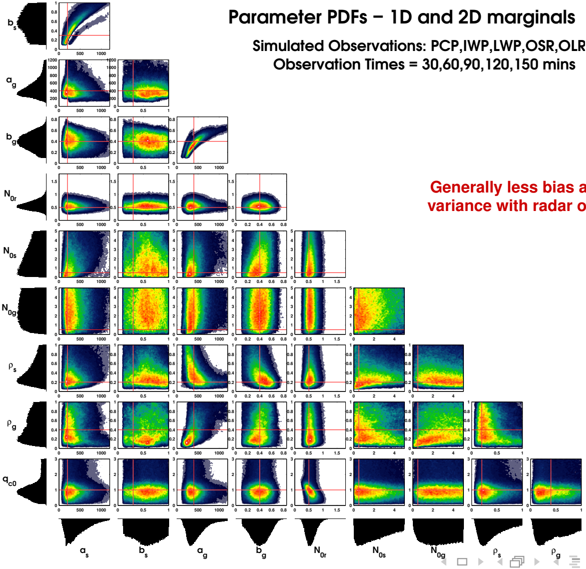
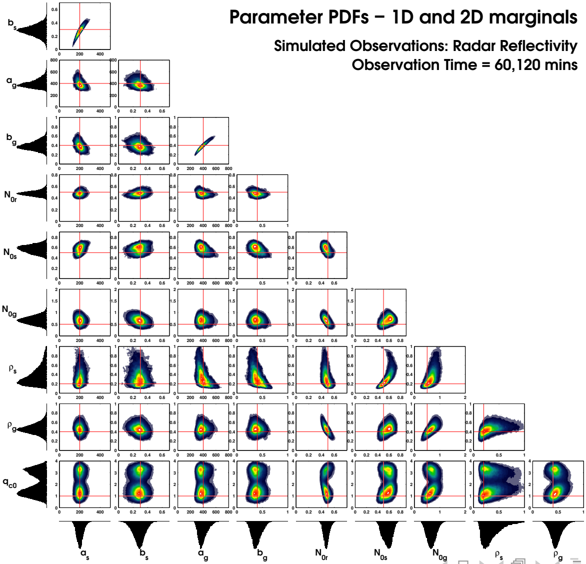


Parameter PDF – column-integral obs.

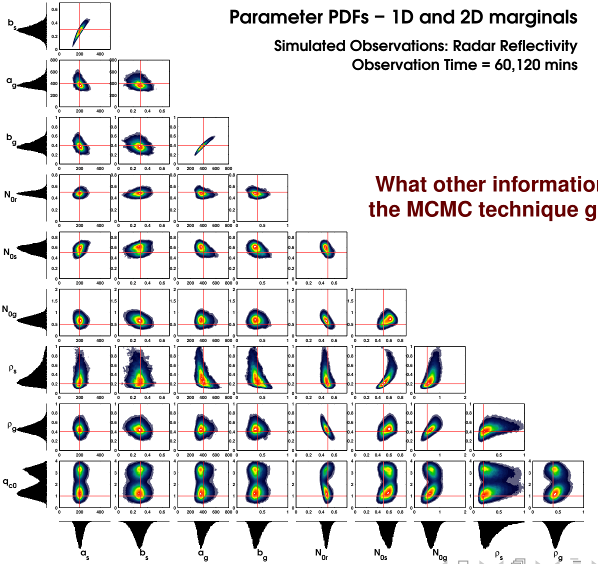


Generally less bias and variance with radar obs.

Parameter PDF – radar obs.

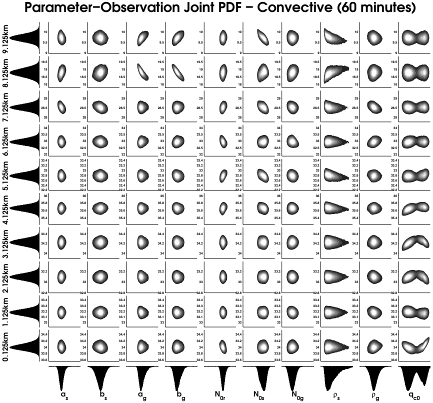


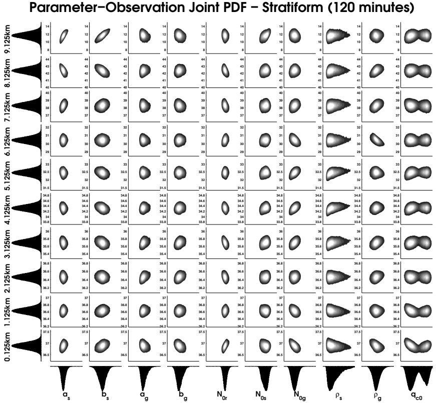
Parameter PDF – radar obs.



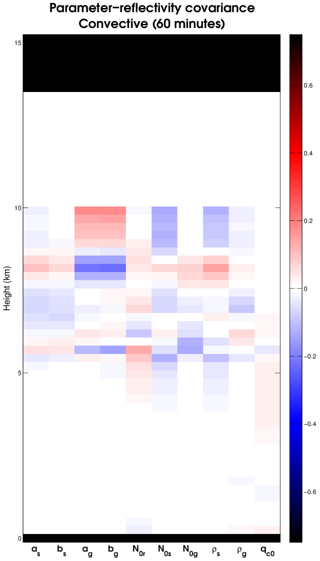
What other information does the MCMC technique give us?

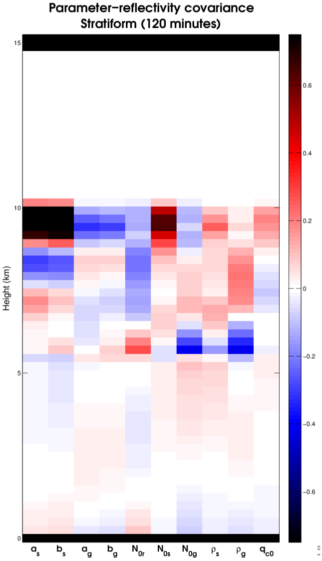
Parameter-Observation Joint PDFs





Parameter-Observation Covariance

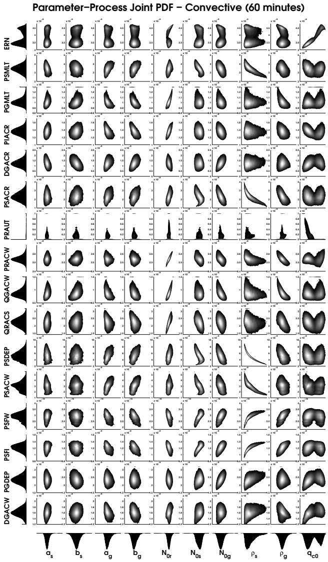


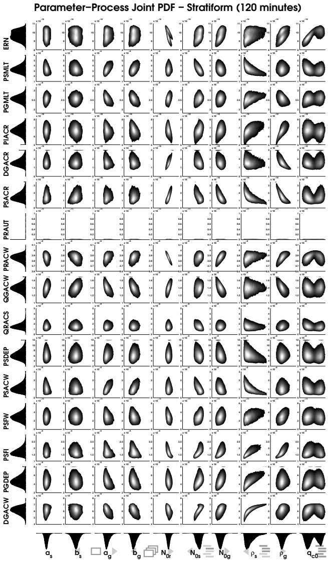


Microphysical Processes

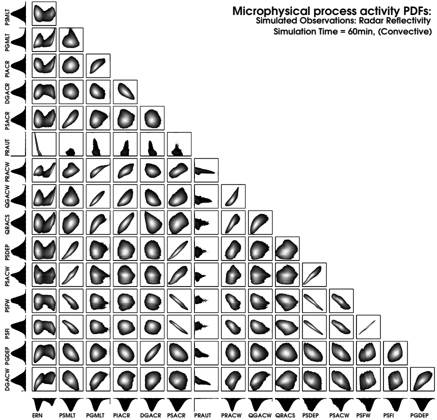
Process description	Abbreviation	Source	Product
Evaporation of rain (negative)	ERN	Rain	Water Vapor
Melting of snow	PSMLT	Snow	Rain
Melting of graupel	PGMLT	Graupel	Rain
Cloud ice accretion of rain	PIACR	Cloud Ice, Rain	Snow, Graupel
Graupel accretion of rain	DGACR	Graupel, Rain	Graupel
Snow accretion of rain	PSACR	Rain, Snow	Snow, Graupel
Autoconversion of cloud water to rain	PRAUT	Cloud water	Rain
Rain accretion of cloud water	PRACW	Rain, Cloud water	Rain
Graupel accretion of cloud water to produce rain	QGACW	Graupel, Cloud water	Rain
Rain accretion of snow	QRACS	Rain, Snow	Rain
Deposition on snow	PGDEP	Water Vapor,Snow	Snow
Snow accretion of cloud water	PSACW	Cloud water, Snow	Snow, Graupel
Bergeron process (deposition/riming)	PSFW	Cloud water	Snow
Deposition on graupel	PGDEP	Water vapor	Graupel
Graupel accretion of cloud water	DGACW	Graupel, Cloud water	Graupel

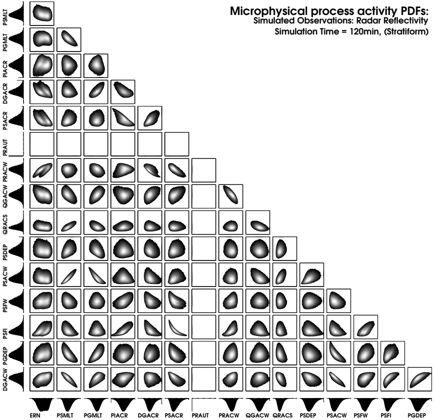
Parameter-Microphysical Process Joint PDFs



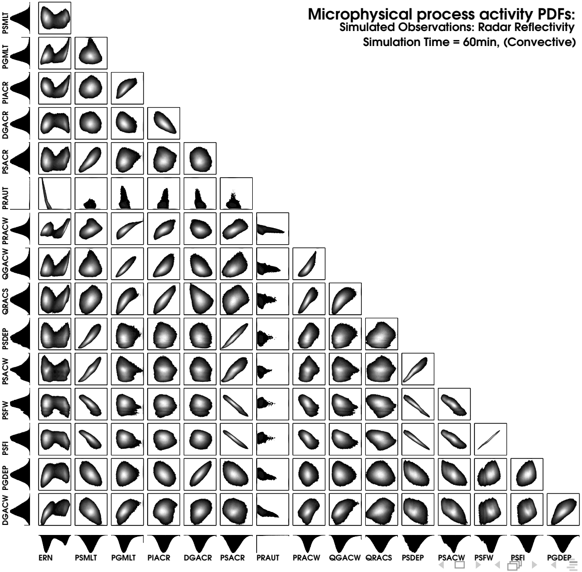


Microphysical Process PDFs

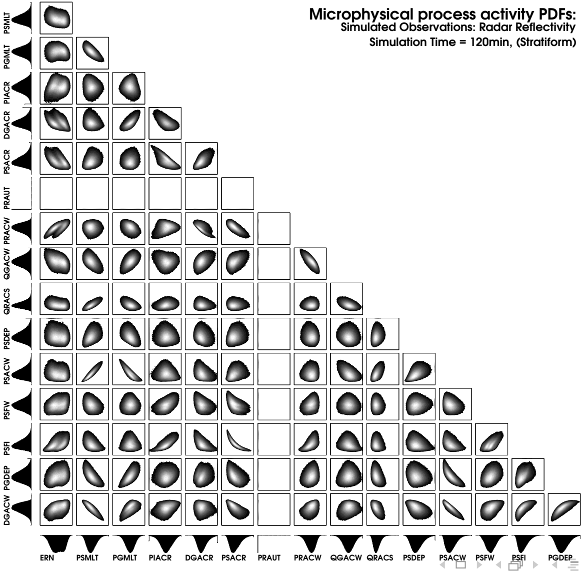




Microphysical Process PDFs – Convective



Microphysical Process PDFs – Stratiform



Summary & Conclusion

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  - Radar observations provide more information to constrain microphysical parameter uncertainty
  - Multivariate relationships between parameters, observations and processes yeilds insight
  - Information for stochastic microphysical parameterization?
- Future work:
  - Perturb processes directly through efficiency parameters
  - Explore more realistic observations/models
  - Advanced MCMC techniques (DRAM, Multinest)

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http://rsmas.miami.edu/personal/mvanlier-walqui