Addressing Non-Guassian Uncertainty in Microphysical Parameterization

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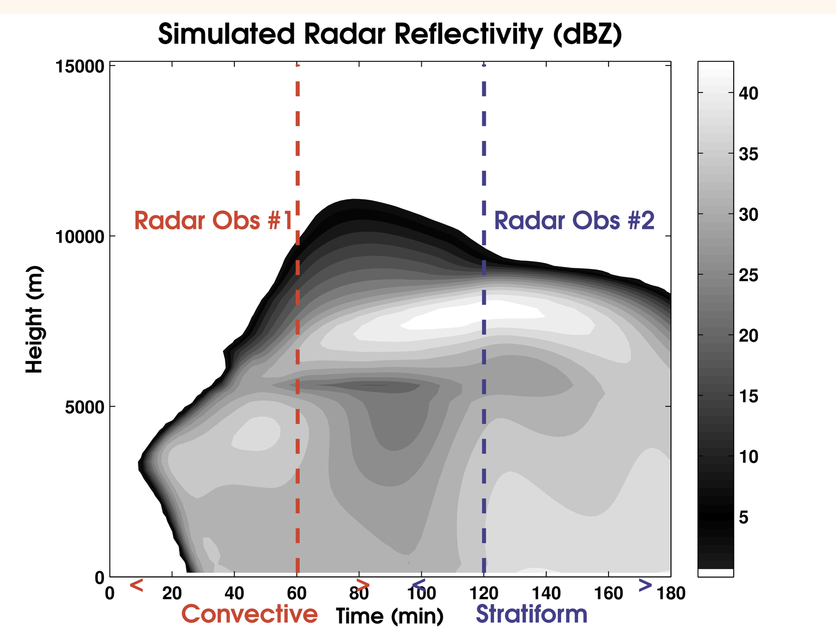
Science Goal

Establish a linear basis for the quantification of microphysical paramerization uncertainty

A consequence of microphysical parameterization is forecast error. In order to correctly predict uncertainty associated with this error, uncertainty in microphysical parameterization must be quantified. It has been found that microphysical parameters have strongly non-Gaussian uncertainty, and so Gaussian inverse methods (such as Ensemble Kalman) are inappropriate. Here, we propose a basis for microphysical parameterization error which we hypothesize has a more linear relationship with forecast quantities.

1D Column Model & Obs



A 1-D idealized atmospheric column model with one moment bulk microphysics [4] is used to simulate microphysical processes present within a squall-line without dynamical or thermodynamical feedback. Simulated radar observations at 60 and 120 mins are produced by the Quickbeam [2] radar forward operator (shown for the "truth" run above). The observation times correspond to the convective and stratiform phases of the simulation.

Simulated radar reflectivity produced in previous experiments [3] are used as a best estimate of model state uncertainty to generate a radar observational error covariance matrix.

Microphysical processes represented within the model have their hydrometeor tendency contributions perturbed by multiplicative perturbation parameters (process parameters, for short). These process parameters form the control parameter basis for the Monte Carlo inversion.

Monte Carlo inversion

A Monte Carlo algorithm is used to draw samples from the probability density function (PDF) in a 12-dimensional process parameter space defined by constraint from vertically resolved radar reflectivity. For more detail, see [3,5].

The MCMC algorithm of [3,5] is modified to a Delayed Rejection, Adaptive Metropolis (DRAM) algorithm [1]. Upon sampler rejection, a more conservative step is proposed and accepted or rejected. Proposal variance is continuously adapted according to points in the Monte Carlo chain. Thus, the algorithm is non-Markovian, but is ergodic (i.e. it samples from the posterior). In addition, a simulated annealing pre-sampler is used to find the main probability mass prior to sampling using DRAM.

Description of Analysis

1. **Posterior parameter PDFs:**
   - Shows relative probability of combinations of values of parameters. Sharp marginal PDFs indicate parameters which are well constrained by observations. Covariance indicates uncertainty which depends on more than one parameter at a time. Symmetry/unimodality indicates that Gaussian inverse methods (e.g. ensemble Kalman) may be applicable.
2. **Joint process parameter/process activity PDFs**
   - Shows control of modeled microphysical behavior (process activity) as as function of the parameters which perturb them.
3. **Bivariate control of process by parameter perturbation**
   - Shows control of process by simultaneous perturbation of two parameters
4. **Information gain and posterior PDFs of column integral variables**
   - Information gain indicates reduction in uncertainty as a result of observational constraint. Posterior distributions show possible bias and/or skewness.
5. **Mahalanobis distance (squared)**
   - Indicates deviations from a Gaussian distribution. Normally distributed samples would give Mahalanobis distance which falls on a line when plotted against chi-square quantile.
6. **Radar reflectivity posterior covariance eigenvalues**
   - Indicates ability of uncertain parameters to capture structure of variability in assumed observation error covariance. The first ten eigenvalues of the posterior distribution of radar reflectivity covariance are shown.

Abbreviations

Process Parameters (current experiment)

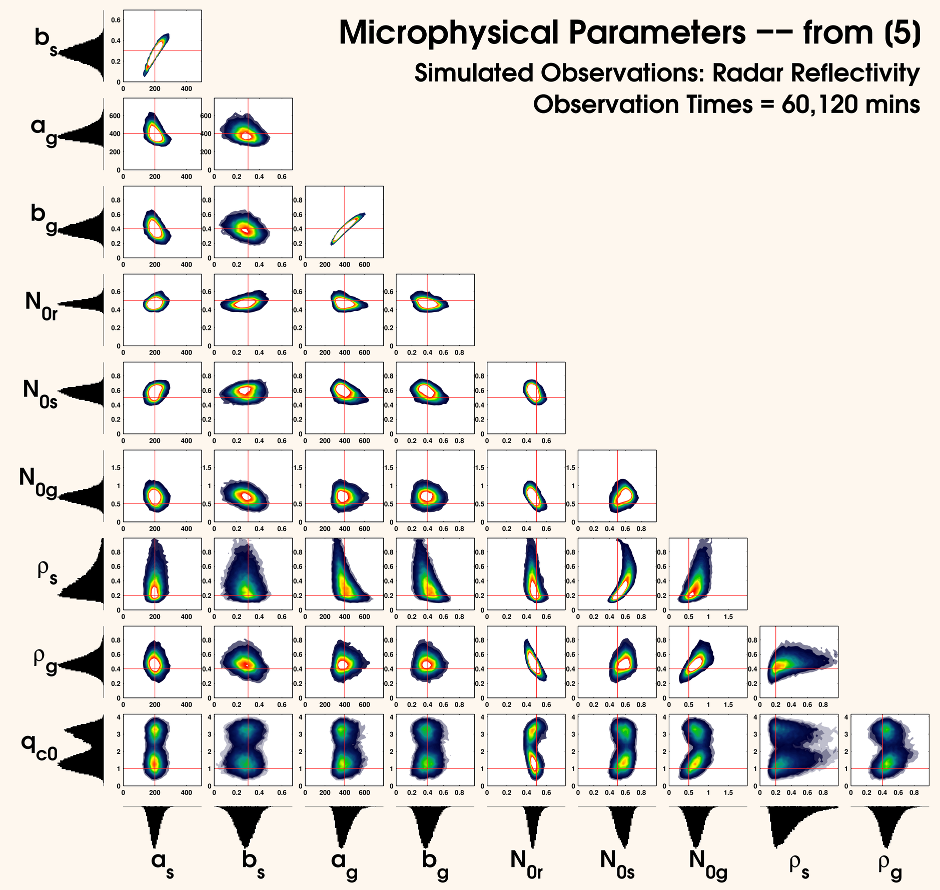
Symbol	Process parameter
ERN	Evaporation of rain
PSMLT	Melting of snow
PGMLT	Melting of graupel
PIACR	Cloud ice accretion of rain
DGACR	Graupel accretion of rain
PRACW	Rain accretion of cloud water
QRACS	Rain accretion of snow
PSDEP	Deposition of vapor on snow
PSFW	Snow growth from cloud water (Bergeron)
PSACR	Snow accretion of rain
DGACW	Graupel accretion of cloud water
PSACW	Snow accretion of cloud water

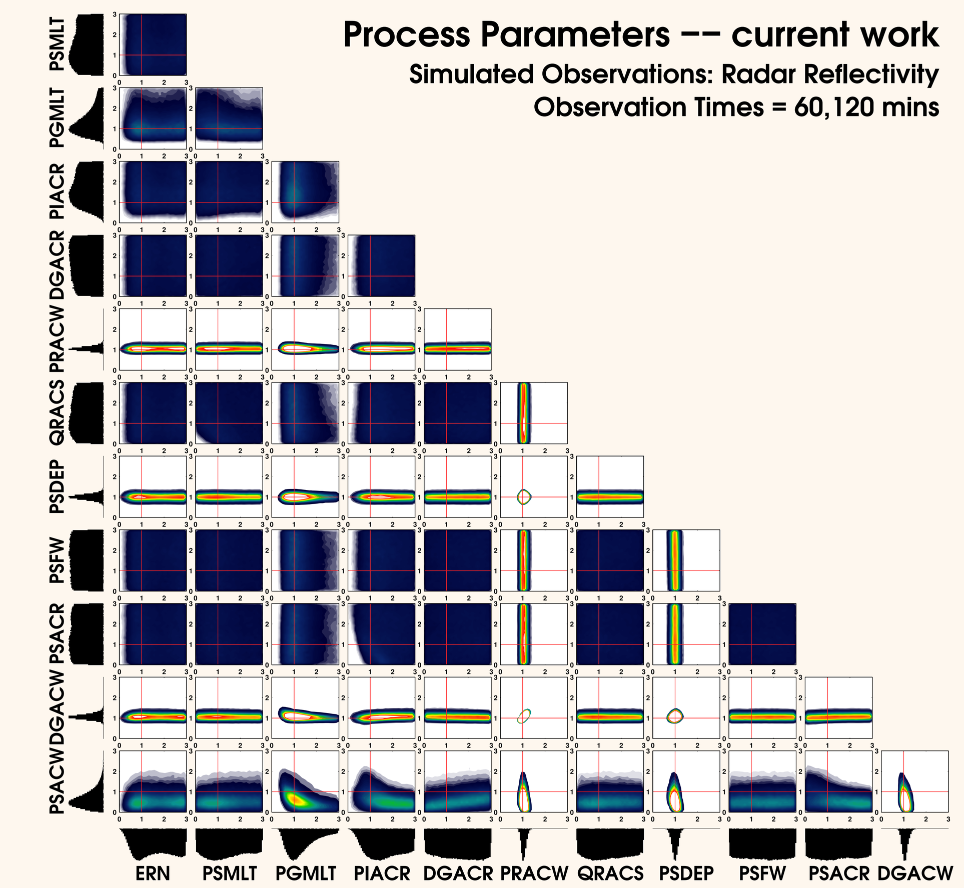
Microphysical Parameters, used in (3,5)

Symbol	Microphysical Parameter
a_s	Snow fall speed coefficient
b_s	Snow fall speed exponent
a_g	Graupel fall speed coefficient
b_g	Graupel fall speed exponent
N_{0r}	Rain PSD intercept parameter
N_{0s}	Snow PSD intercept parameter
N_{0g}	Graupel PSD intercept parameter
ρ_s	Snow particle density
ρ_g	Graupel particle density
q_{c0}	Cloud/rain conversion threshold

Results

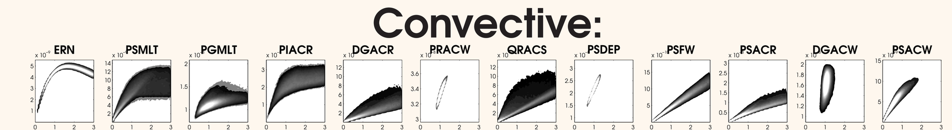
1. Posterior parameter PDFs (1D & 2D marginals)



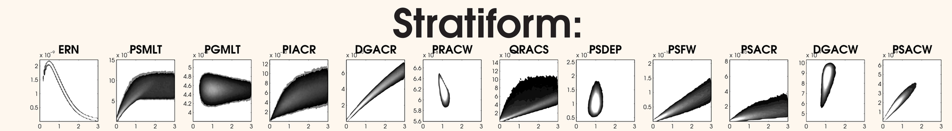


2. Process parameter – process activity joint PDFs

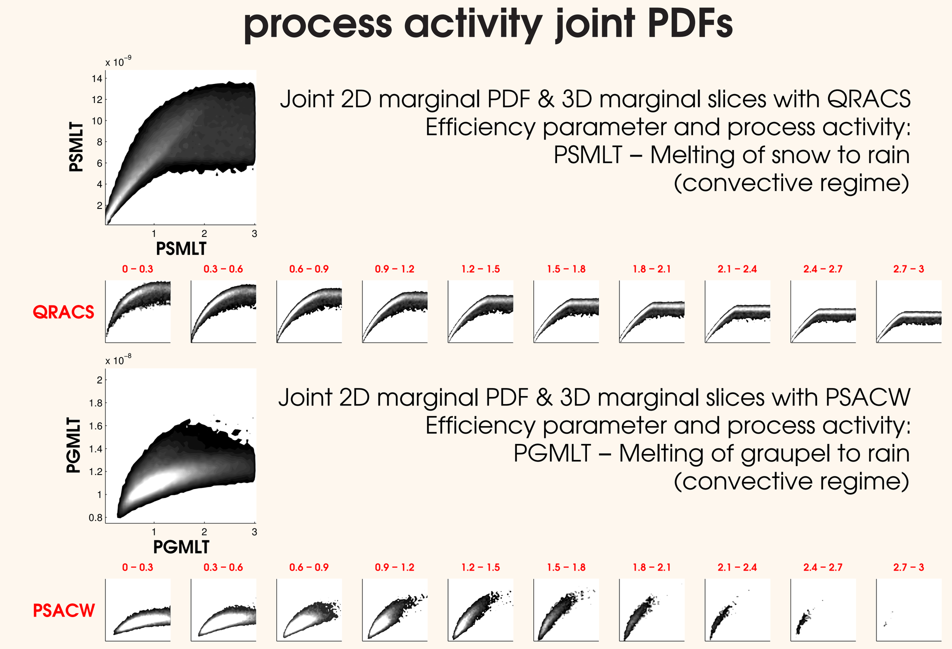
Convective:



Stratiform:

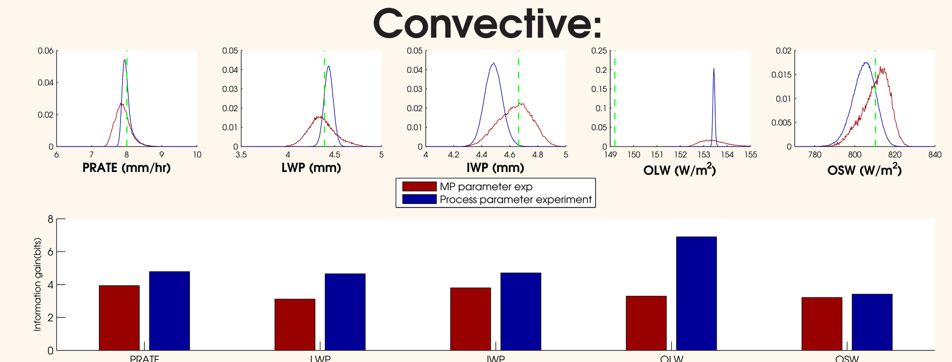


3. Bivariate control of process parameter – process activity joint PDFs

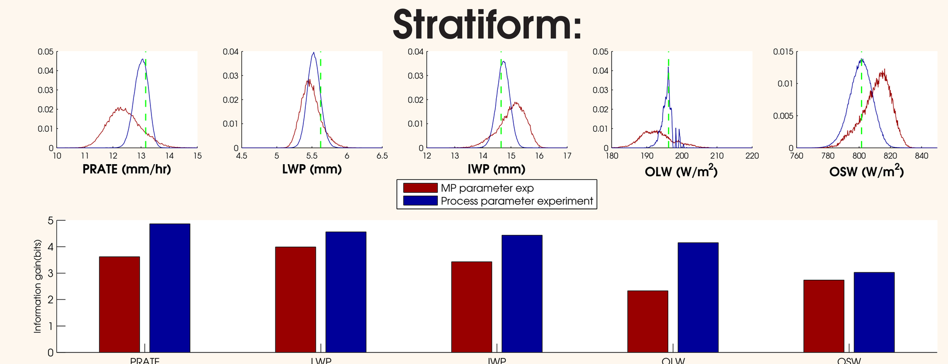


4. Information gain and posterior PDFs for model output

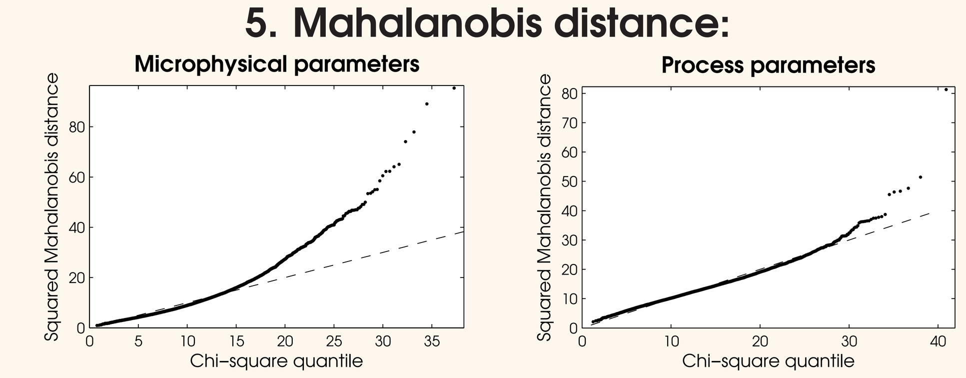
Convective:



Stratiform:



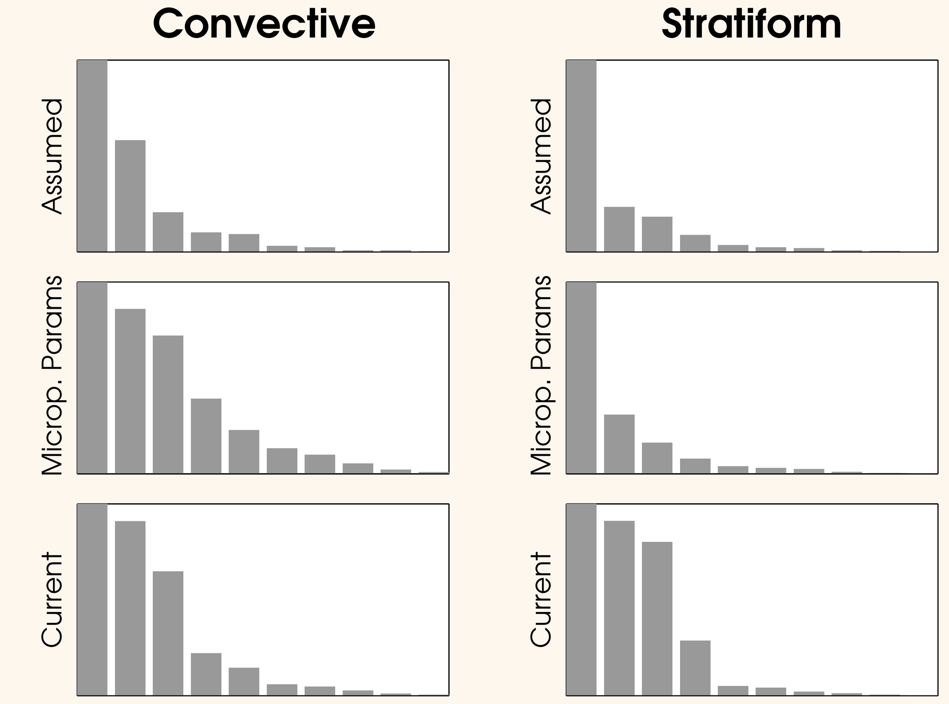
5. Mahalanobis distance:



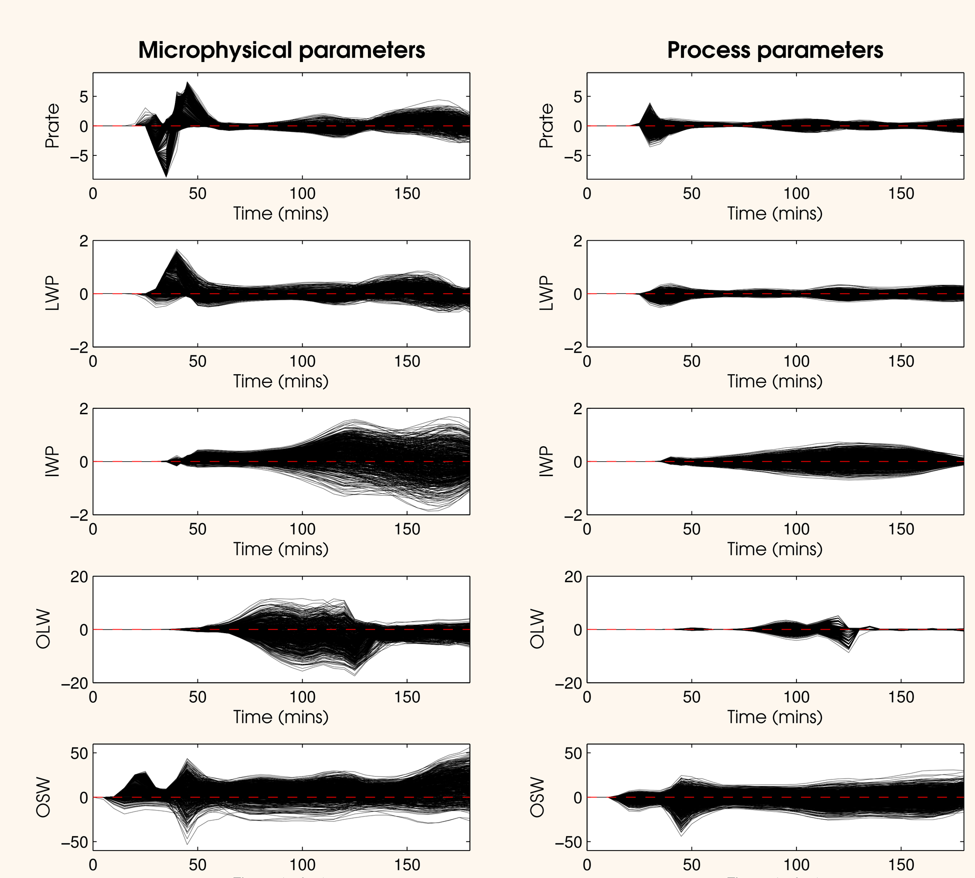
Skewness = 22.46
Kurtosis = 146.3

Skewness = 6.085
Kurtosis = 164.5

6. Radar reflectivity posterior distribution eigenvalues:



7. Time evolution of column-integral obs.



Conclusions

- Multiplicative process parameters provide new basis to represent microphysical parameterization uncertainty (see result 1)
- Posterior distributions of process parameters show skewness and multimodality and some appear near-uniform (see result 1)
- Joint process parameter-process activity PDFs show some degree of linear control (see result 2)
- Process parameter control of process activity shows some consistency between simulated storm regimes (see result 2)
- Even parameters which are not well constrained show *bivariate* control, that is, together with perturbation in another parameter (see result 3)
- Information gain on column-integral variables indicates reduction of uncertainty using process parameters compared with microphysical parameters. Posterior distributions indicate reduced bias, particularly in the stratiform simulated storm morphology (see result 4)
- Mahalanobis distance indicates that the process parameter posterior PDF is much closer to Gaussianity than microphysical parameter posterior PDF of [5]. (see result 5)
- Analysis of structure of radar forward observation covariance indicates that microphysical parameters capture structure of vertical variability better than process parameters, particularly for the stratiform simulated storm regime. (see result 6)

Future work

- Test hypothesis by using Ensemble Transform Kalman Smoother (EnTKS) in parameter estimation experiment with both microphysical parameters and process parameters
- Test log-scaled process parameters, to respect positive definiteness of parameter space and address high skewness of posterior parameter PDF.
- Implement truncated Gaussian statistics into EnTKS to alleviate problems with high kurtosis of posterior parameter PDF.

References

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