Cloud Process Nonlinearity and Model Uncertainty in Data Assimilation and Remote Sensing

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INTRODUCTION

Assimilation of remote sensing observations of clouds and precipitation is challenging:

- Nonlinearity in: cloud and precipitation processes, relationships among state variables, and relationships between state and observations
- Large spatial and temporal variability in cloud features, leading to large forecast-observation innovations
- Parameterizations of cloud processes with poorly understood and state-dependent uncertainty

New observing systems and new data assimilation algorithms offer pathways forward:

- Quantification of uncertainty in cloud microphysical parameterizations
- New data assimilation algorithms for positive definite quantities and nonlinear cloud processes
- Adaptive ensemble techniques that make use of high time frequency geostationary satellite data for constraint of isolated and organized convective systems

ACCOUNTING FOR MODEL ERROR AND NONLINEARITY IN DATA ASSIMILATION

Modern data assimilation algorithms are rooted in Bayes' relationship. $p(\mathbf{x}\,|\,\mathbf{y}) \propto p(\mathbf{y}\,|\,\mathbf{x})\,p(\mathbf{x})$ **Representation of uncertainty (via probability distributions) is crucial.**

Nonlinearity introduces complexity: Approximate solutions to Bayes' relationship assume linearity and/or Gaussianity. Nonlinearity leads to departures from Gaussianity. → Evaluate quasi linear algorithms and develop new nonlinear DA methodologies

Observation error: is due to measurement uncertainty and also to uncertainty in instrument simulators: This source of uncertainty can be difficult to characterize.

Model error: due to approximations in cloud and precipitation processes is commonly nonlinear and state dependent.

→ Use a reference Bayesian solution (MCMC) to quantify forward model and model parameterization uncertainty, and to assess parameter identifiability

Model-observation mis-match: due to cloudy model and clear observation (and vice versa) violates linearity assumptions. → Use state-dependent observation and background error inflation and high time resolution observations

MEASUREMENT SIMULATION UNCERTAINTY P(y|x)

Experiment Configuration and Goals

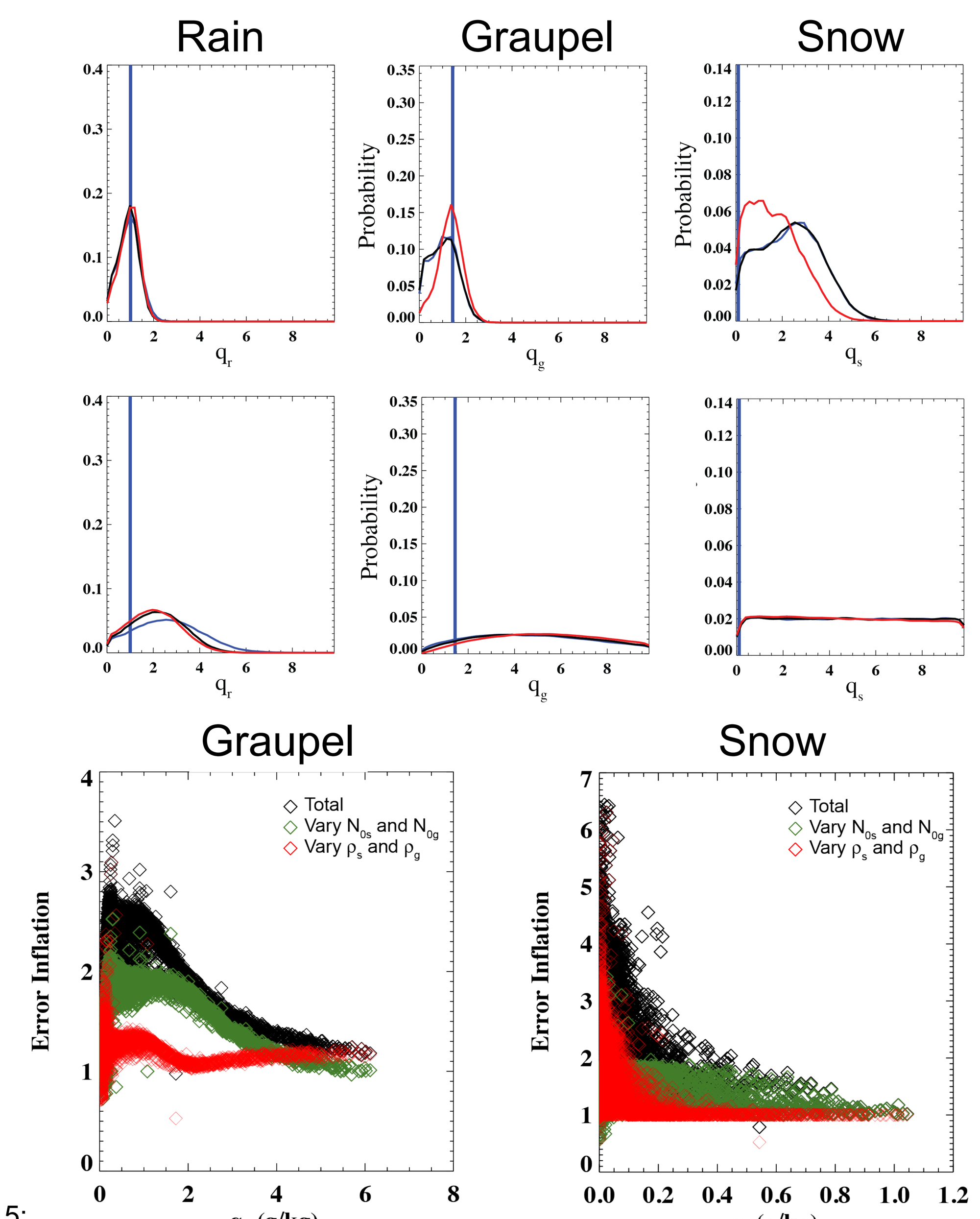
- Forward model radar variables from known cloud hydrometeor content
- Estimate cloud content from radar using an MCMC algorithm assuming a perfect model
- Estimate cloud content using variable PSD assumptions (imperfect model)
- Quantify increase in uncertainty due to model error

$$p(\mathbf{y}\,|\,\mathbf{x}) = p(\mathbf{y}\,|\,\mathbf{x}_t)\,p(f(\mathbf{x})\,|\,\mathbf{x})$$

Likelihood — Instrument Error — Forward Model Error

Outcomes

- Changes in PSD assumptions have a strong, and state-dependent effect on the uncertainty in observations
- Variability in PSD assumptions increases uncertainty by up to 3x



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MODEL PARAMETERIZATION UNCERTAINTY P(x)

Experiment Configuration and Goals

- Simulate cloud and precipitation profiles using a cloud resolving model
- Quantify effect of changes to microphysics parameters on model output using an MCMC algorithm
- Determine degree of (non)linearity in parameter – model output relationships

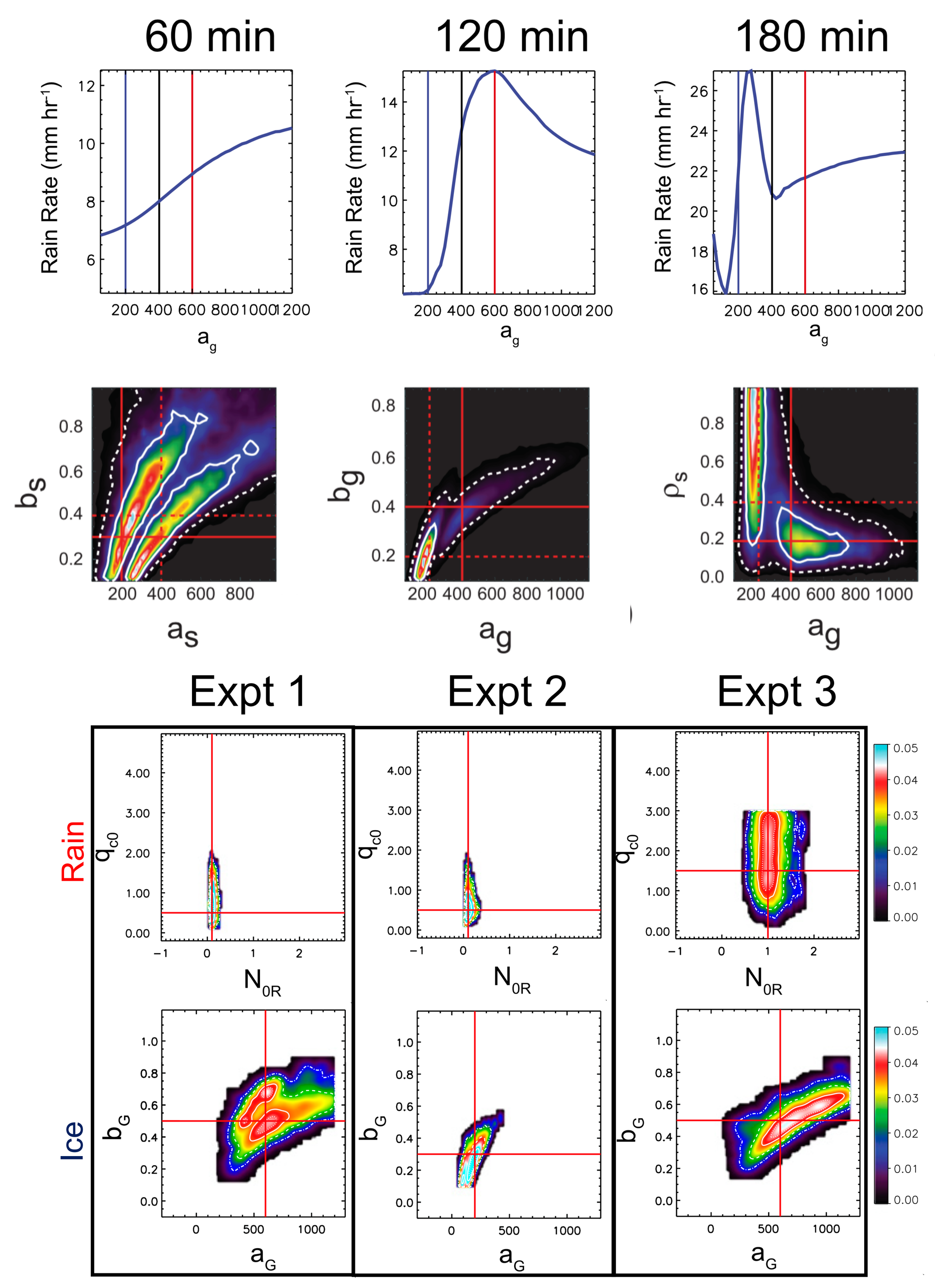
Outcomes:

Model error is nonlinear

- Monotonic: single probability maximum
- Non-monotonic: multiple maxima

Nonlinearity is state-dependent

- More evident in stratiform regions / later times than convective / early times
- Depends on "true" value of parameters
- Parameter – model output relationships are non-unique



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NONLINEAR DATA ASSIMILATION ALGORITHMS

Experiment Configuration and Goals

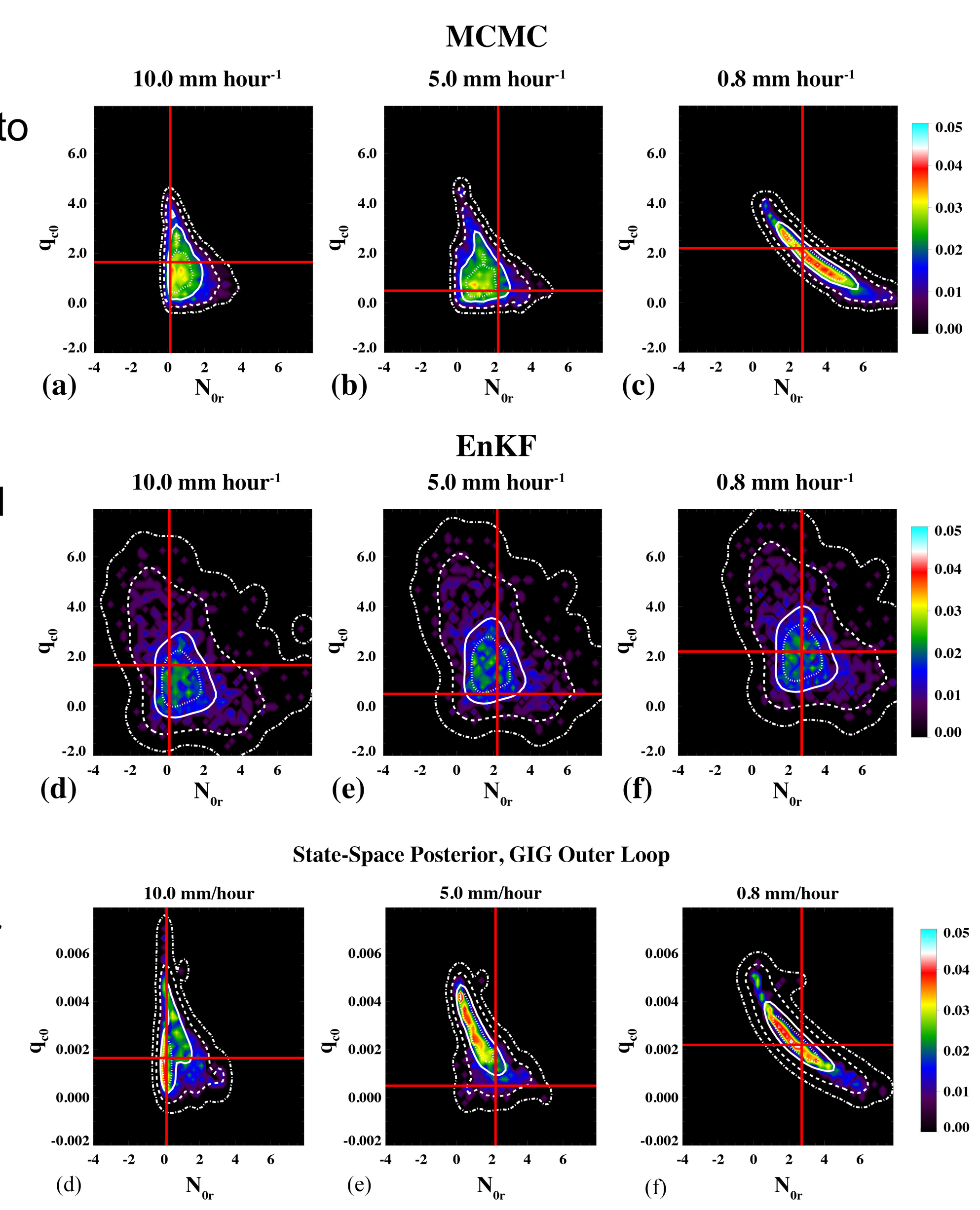
- Cloud variables are nonlinearly related to observations and positive definite
- Observation error is often a *fraction* of the observation value (% error vs fixed)

Evaluate data assimilation algorithms for nonlinear and positive definite quantities

- MCMC serves as a reference
- Compare EnKF with recently developed Gamma Inverse-Gamma (GIG) filter

Outcomes

- Reference (MCMC) posterior distributions show positive definite and state-dependent nature of cloud parameters
- EnKF re-centers posterior density according to observations, but posterior variance is unchanged and negative solutions are allowed
- GIG solution is positive definite and state dependent



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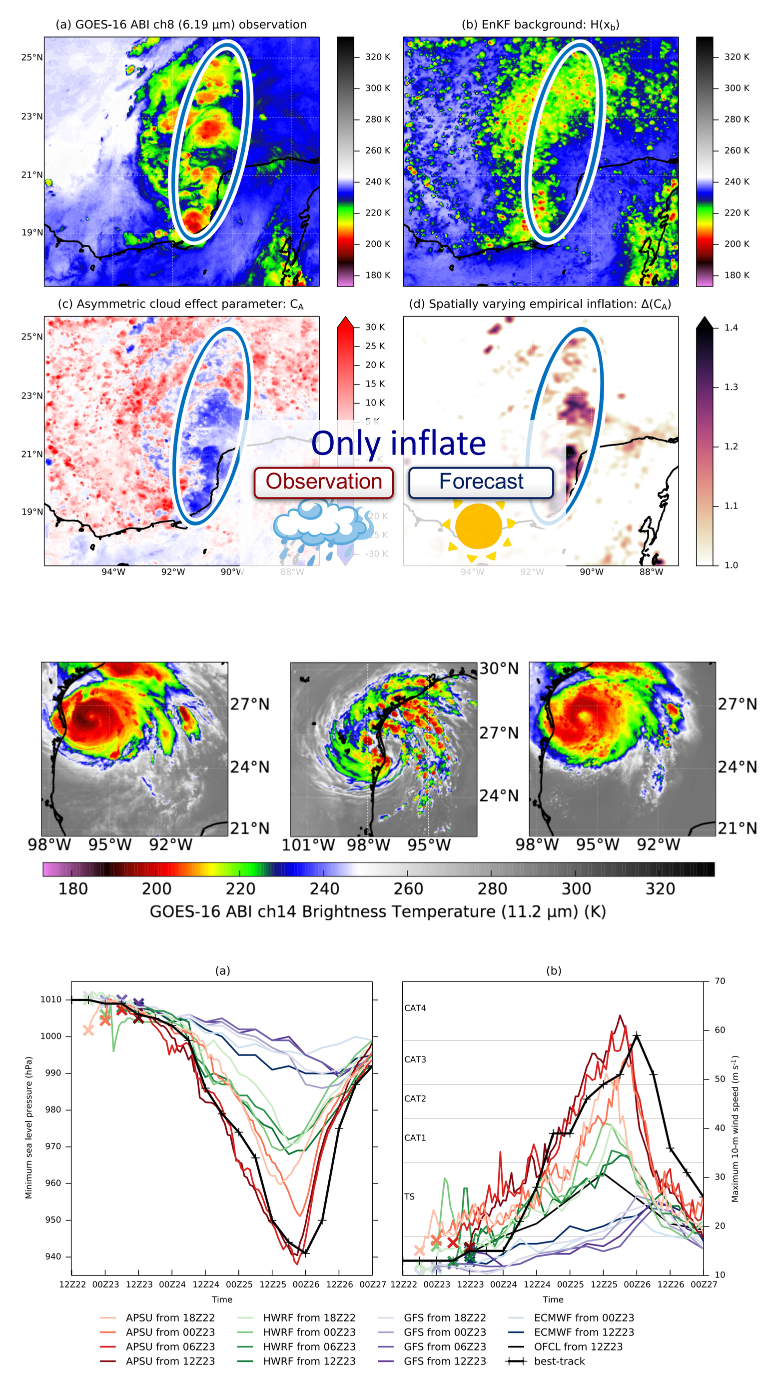
ALL-SKY SATELLITE RADIANCE DATA ASSIMILATION

Experiment Configuration and Goals

- Model: WRF version 3.6.1; 27,9,3 km grid spacing; ensembles of hurricane Harvey (2017) simulations
- PSU EnKF system with 60 members
- Assimilate all-sky geostationary water vapor radiances at 15 minute intervals
- Inflate background and observation errors in regions with large mis-match between observation and model (large innovation) via cloud flag
- Inflate only where model = clear and obs = cloudy

Outcomes

- Assimilation of water vapor channels significantly improves WRF analysis and forecast – an indication of the importance of environmental RH and proper cloud position
- Assimilation of all-sky brightness temperatures has a significant effect on TC intensity
- Assimilation of water vapor radiances prior to rapid intensification leads to ability to capture intensification accurately



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