

Dual-Polarimetric Radar Data Assimilation and Information Content Analysis Study

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Dual-Polarimetric Radar

Horizontal and vertical signals: more info about the type, shape, and size of the hydrometeors – more accurate estimates of precipitation and cloud particles.

Standard Variables from ARMOR (C-band):

Z_H : Horizontal reflectivity

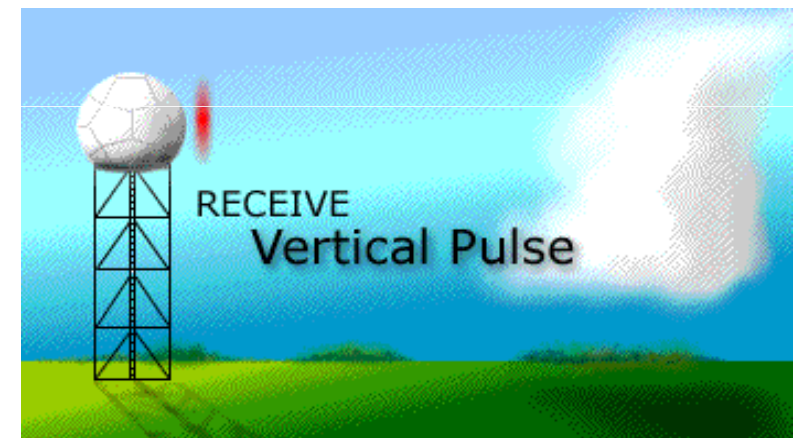
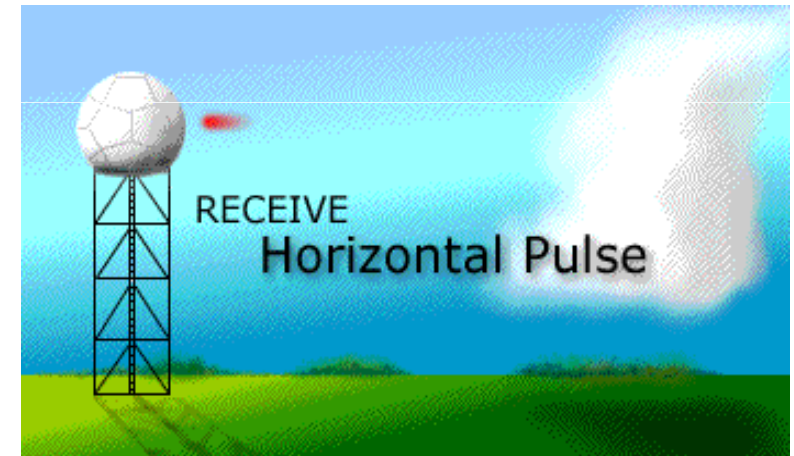
V_R : Radial velocity

Z_{DR} : Differential reflectivity $Z_{DR} = 10 \log_{10}(Z_H/Z_V)$

K_{DP} : Specific differential phase, range derivative of Φ_{DP}

ρ_{HV} : Correlation coefficient, the coefficient between the horizontal and vertical power returns.

Φ_{DP} : Differential phase, the measured phase shift between horizontal and vertical pulses



Motivation and Goals

- *Only a few* studies have been done assimilating real dual polarimetric data in storm scale forecasting:
 - Wu et al. (2000) indirectly assimilated Z_{DR} .
 - Jung et al. (2008; 2010) assimilated Z_{DR} , K_{DP} in OSSEs.
- NWS upgrades current NEXRAD radar network to include dual-polarization capabilities (2012-2014). Migrate to use of S-band data.
- Project goal is to assimilate dual-pol Doppler radar observations for real cases and seek better performance in radar data assimilation.
- Examine how and by how much the dual-pol variables influence the initial fields, the sensitivity of radar data assimilation to operator.
- Investigate information content for dual-pol radar variables

Model & Radar Data Assimilation Package

- WRF ARW v3.0
- WRF 3DVAR system
- Warm-rain forward operator
- Cycled assimilation of ARMOR data

Radar Forward Operators

$$V_R: \quad VR = u \frac{x - x_i}{r_i} + v \frac{y - y_i}{r_i} + (w - v_T) \frac{z - z_i}{r_i}$$

$$Z_H \text{ Only:} \quad Z_H = 2.04 \times 10^4 q_r^{1.75}$$

$$Z_H \text{ and } Z_{DR}: \quad q_r = 0.6 \times 10^{-3} \times Z_H^{0.85} \times \mathfrak{S}_{DR}^{-2.36}$$

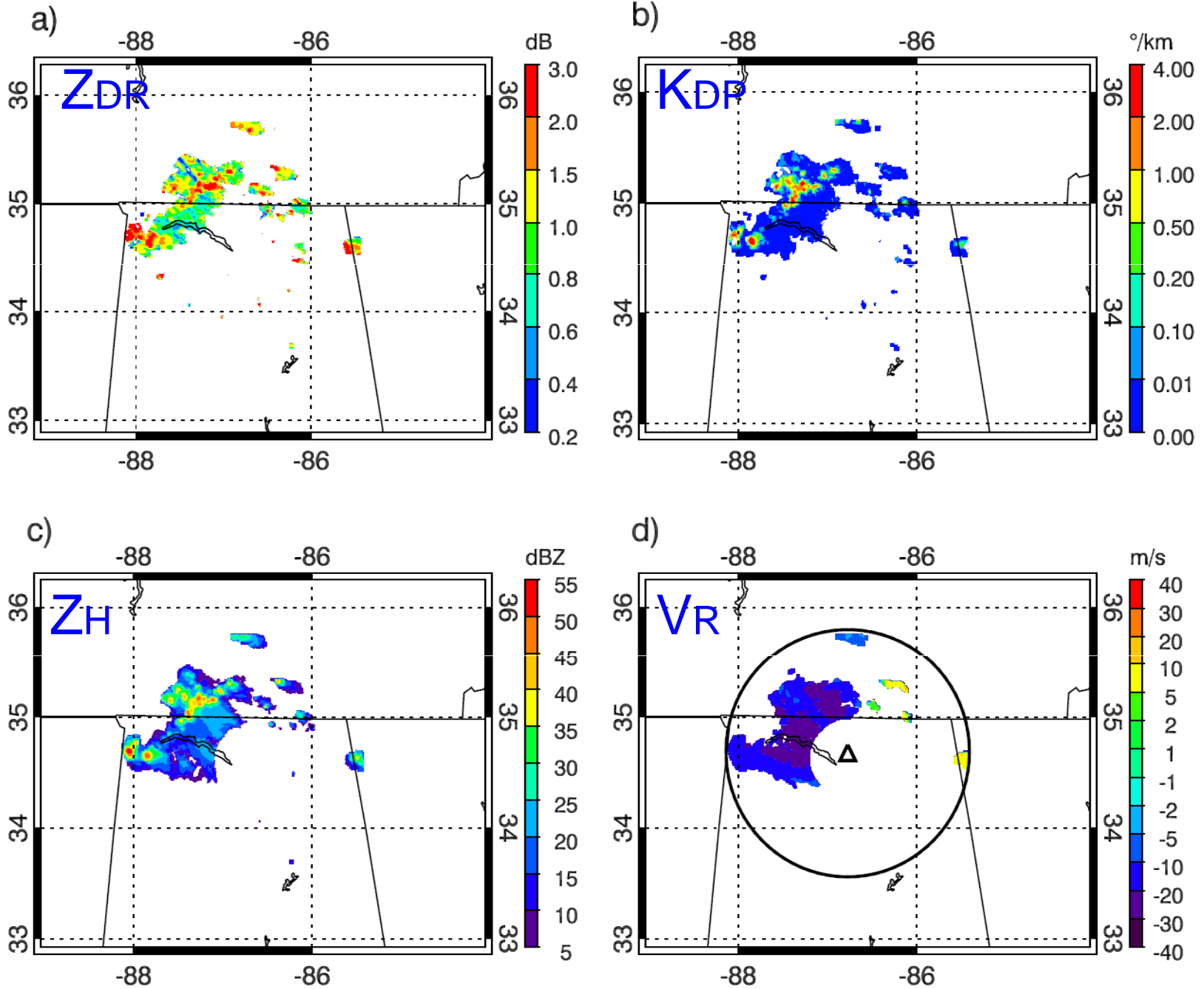
\mathfrak{S}_{DR} : non-dimensional differential reflectivity in linear scale

Comparison of K_{DP} and Z_{DR} assimilation:

$$\text{Ryzhkov and Zrnić (1995):} \quad q_r = 3.11 \times K_{DP}^{0.918} \times Z_{DR}^{-0.764}$$

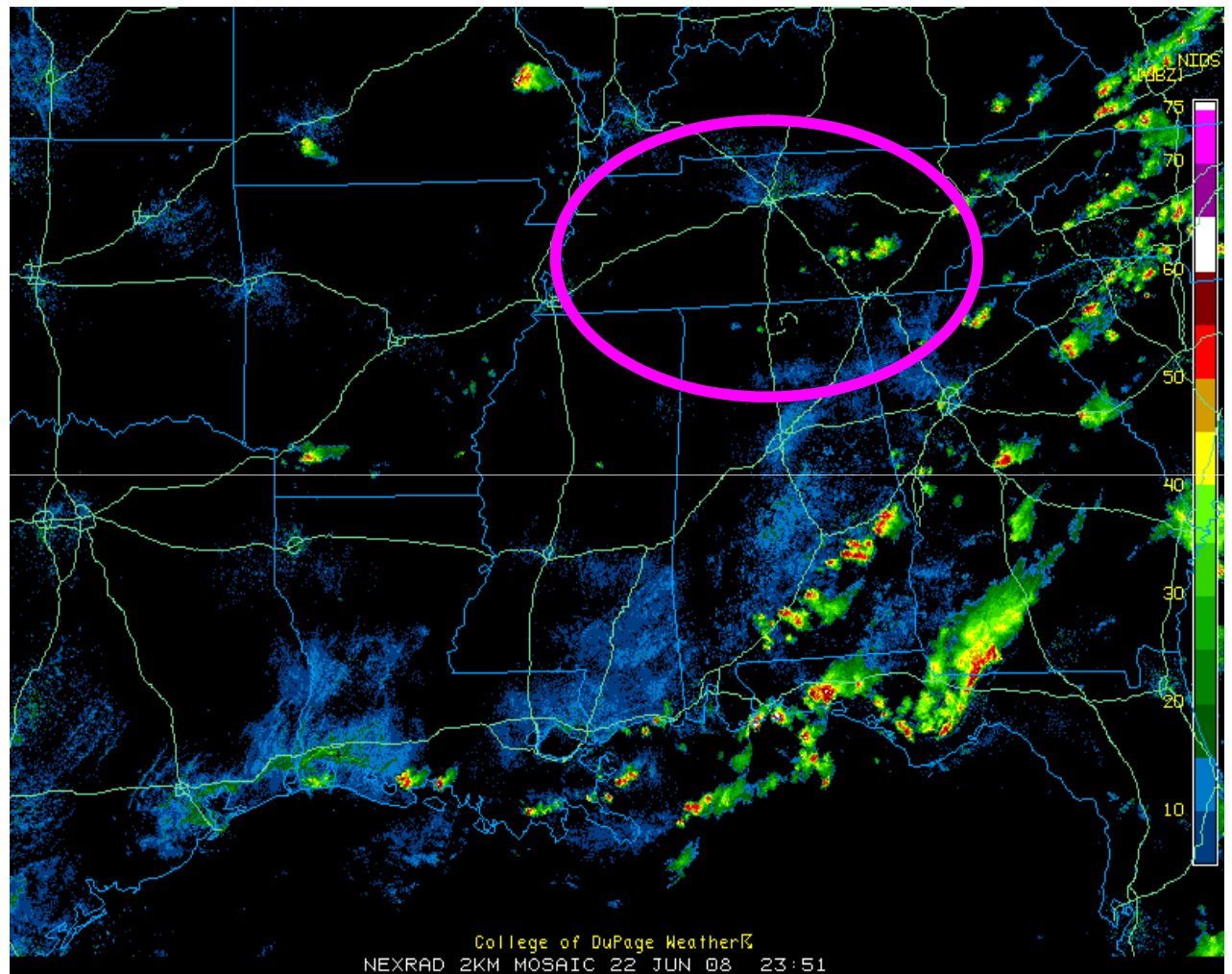
$$\text{Bringi and Chandrasekar (2001):} \quad q_r = 2.32 \times K_{DP}^{0.83} \times \mathfrak{S}_{DR}^{-1.11}$$

Sample ARMOR Data: 1930 UTC 23 June 2008



Case Study

23 June 2008

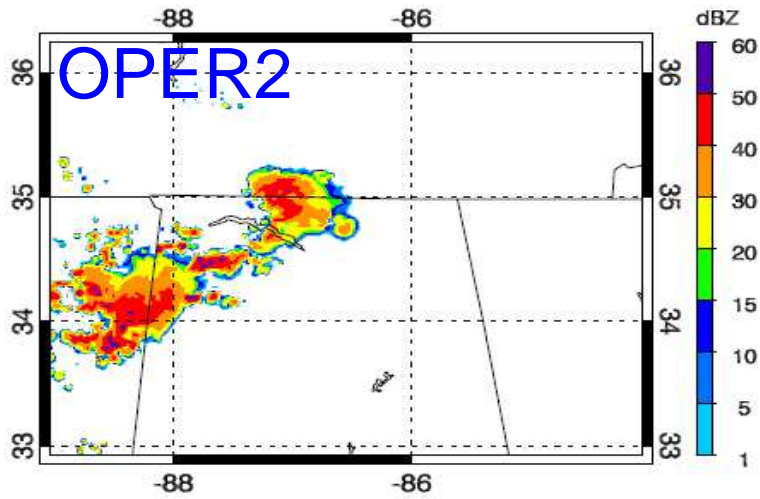
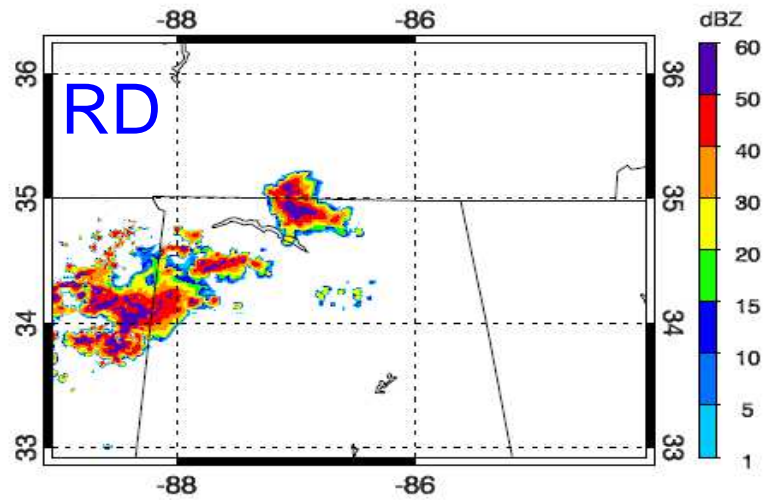
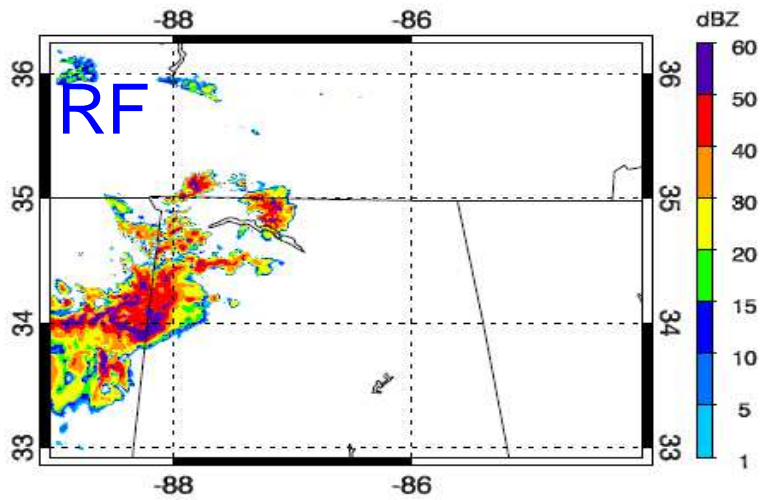
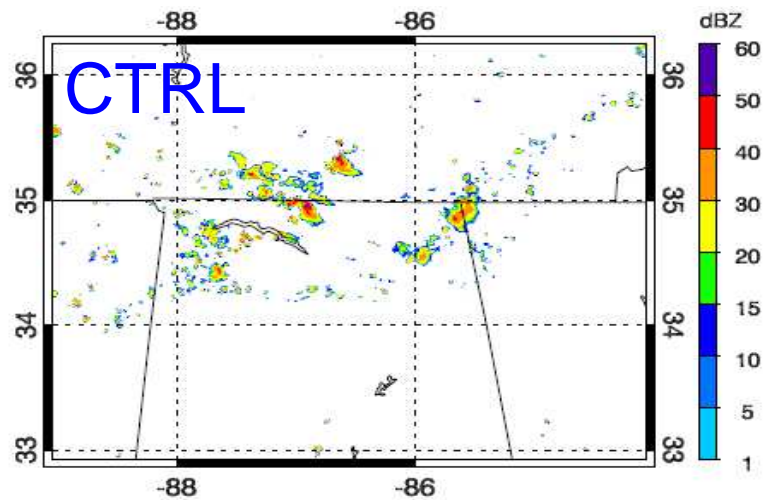
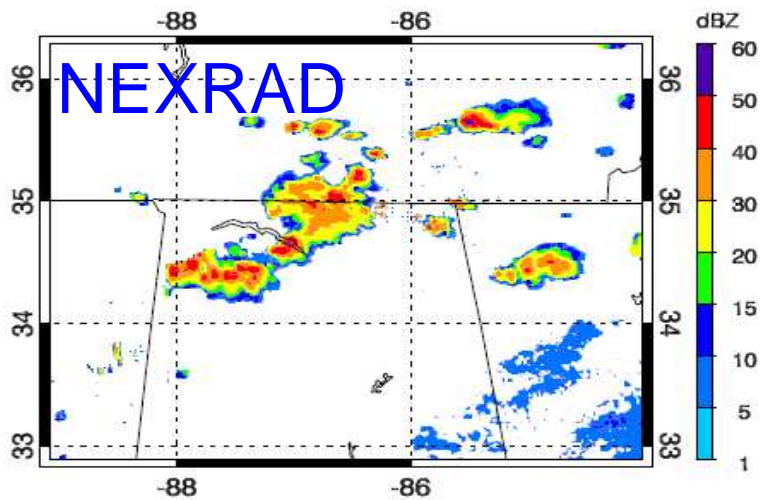


Thunderstorm in the afternoon over southern Tennessee and northern Alabama.

Storm was within ARMOR radar coverage for much of its lifetime, making it ideal for analysis in a data assimilation framework.

Data Assimilation Experiments

Experiment	ARMOR Data Assimilation	Variables
CTRL	N/A	N/A
RF	1930, 2000, 2030 UTC 23 June 2008	Z _H
RD	1930, 2000, 2030 UTC 23 June 2008	Z _H and Z _{DR}
OPER1	1930, 2000, 2030 UTC 23 June 2008	K _{DP} and Z _{DR} (Ryzhkov and Zrnice 1995)
OPER2	1930, 2000, 2030 UTC 23 June 2008	K _{DP} and Z _{DR} (Bringi and Chandrasekar 2001)

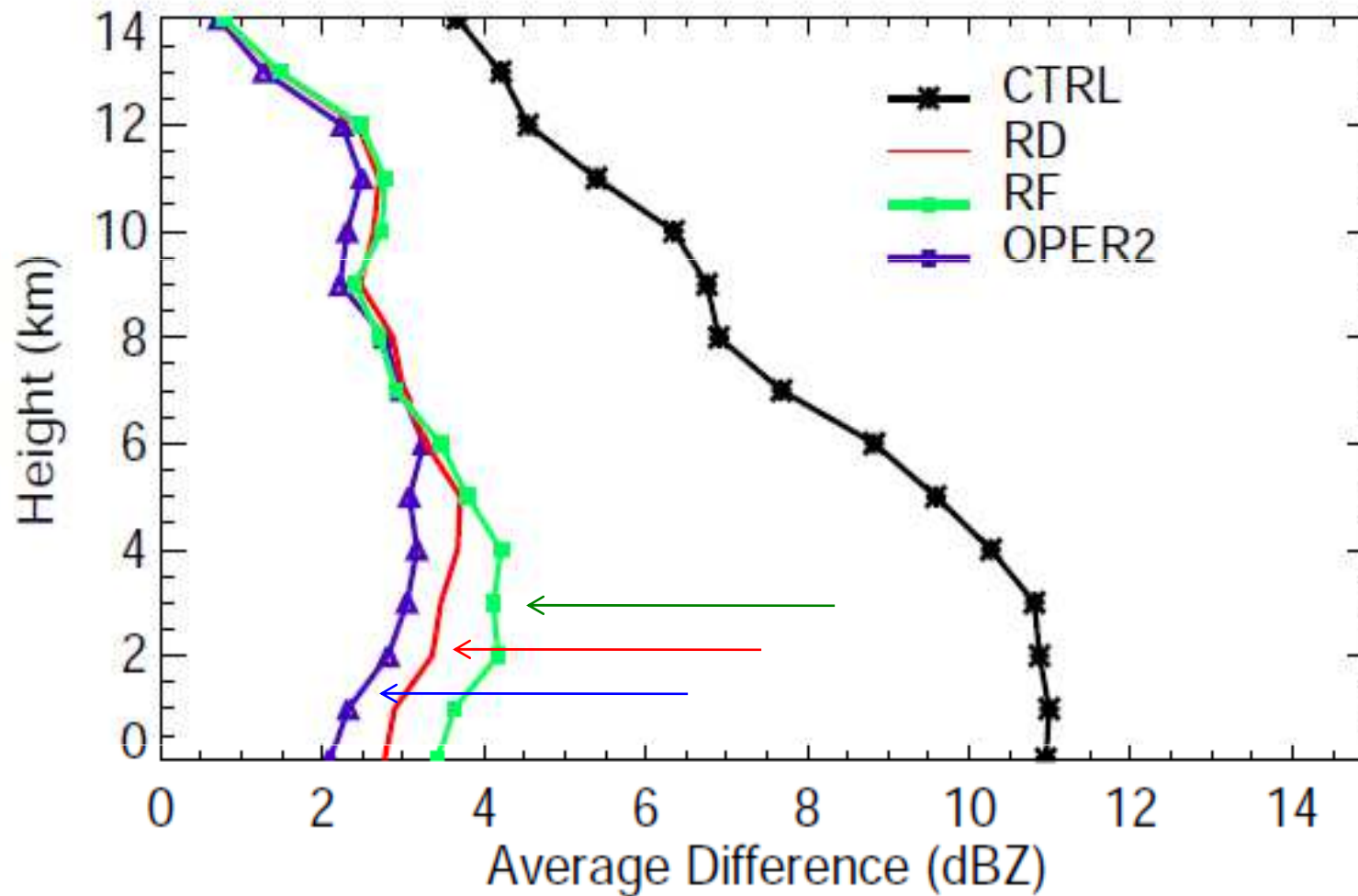


Reflectivity 2030 UTC 23 June 2008:

K_{DP} and Z_{DR} data assimilation (**OPER2**) produces better initialization than Z_H and Z_{DR} assimilation (**RD**) and Z_H -only assimilation (**RF**).

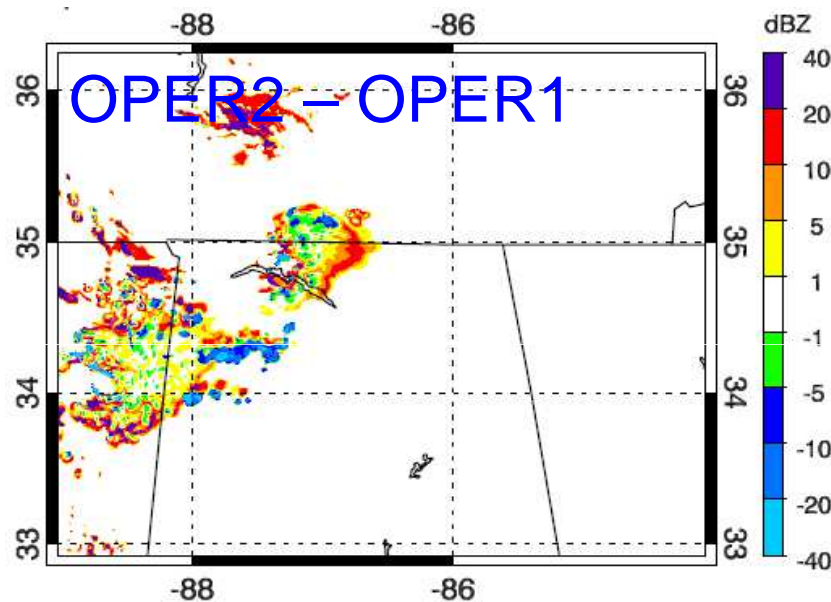
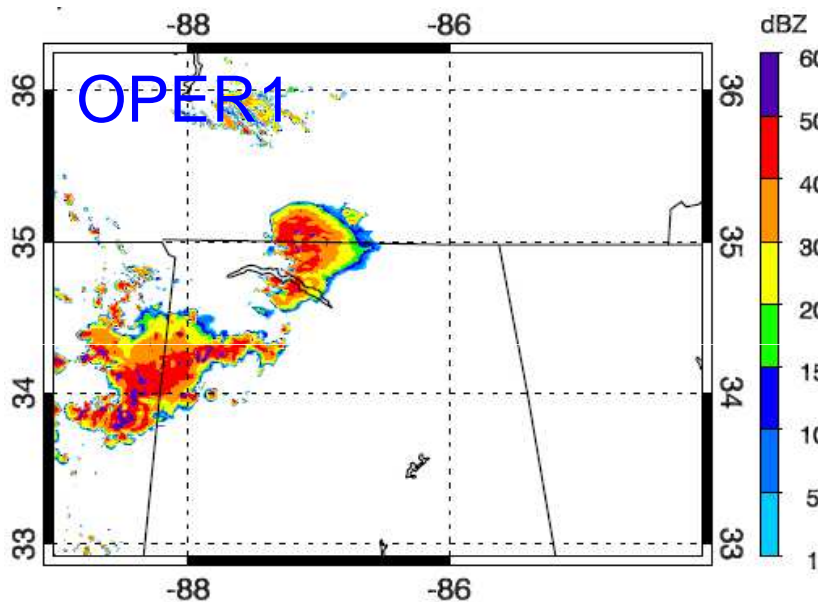
Warm rain processes being better represented.

O-B (CTRL) & O-A (RD, RF, OPER2) Comparisons

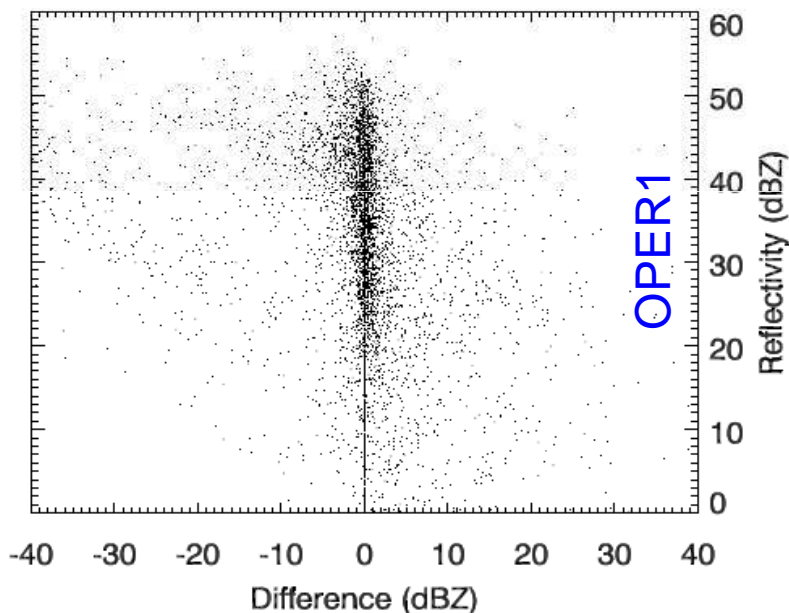


K_{DP} and Z_{DR} data assimilation (**OPER2**): Produces around 10-20% lower O – A value than **RF** and **RD** experiments. The O – B differences from **CTRL** show that the storm is mostly not captured.

K_{DP} and Z_{DR} Data Assimilation Comparison:



e)



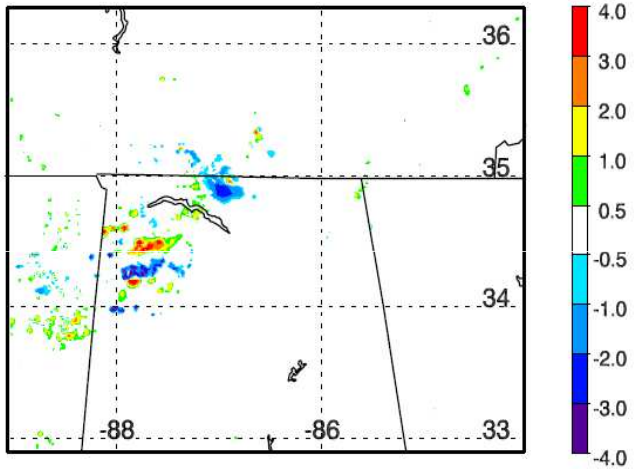
OPER2 - OPER1

OPER2 vs. OPER1:

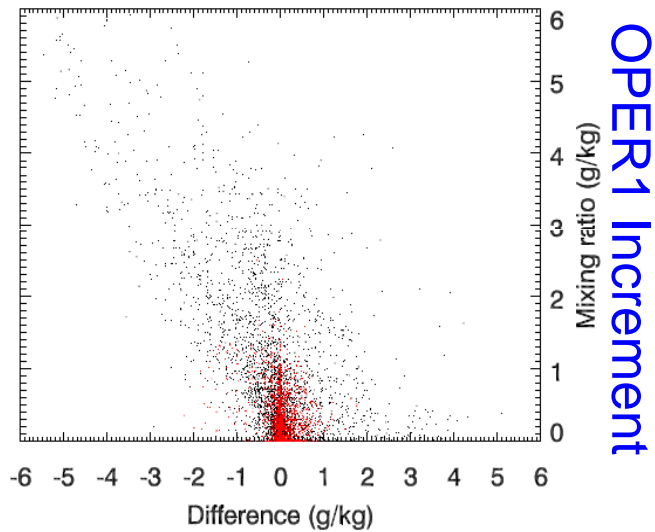
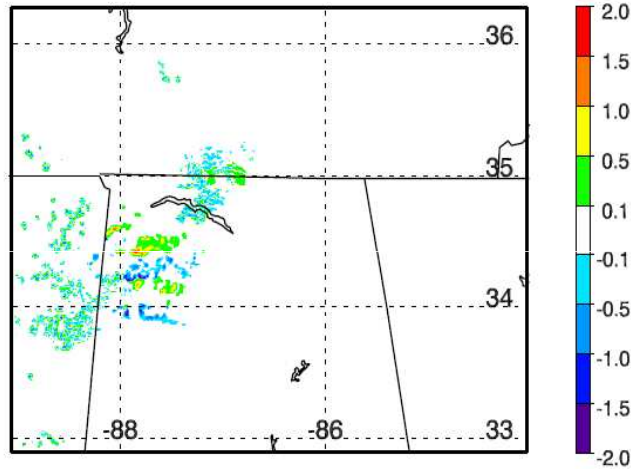
Similar storm location and less water (negative values) at high reflectivity region in OPER2 versus in OPER1.

Data Assimilation: OPER1 – OPER2

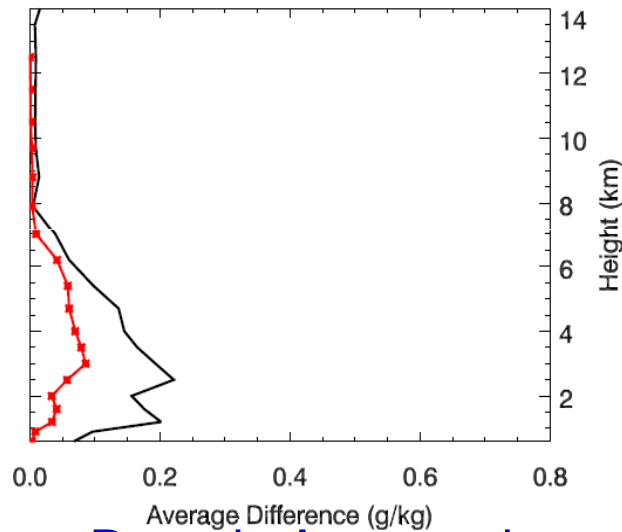
Rain Water



Cloud Water



OPER2-OPER1



Domain Averaged
OPER2-OPER1

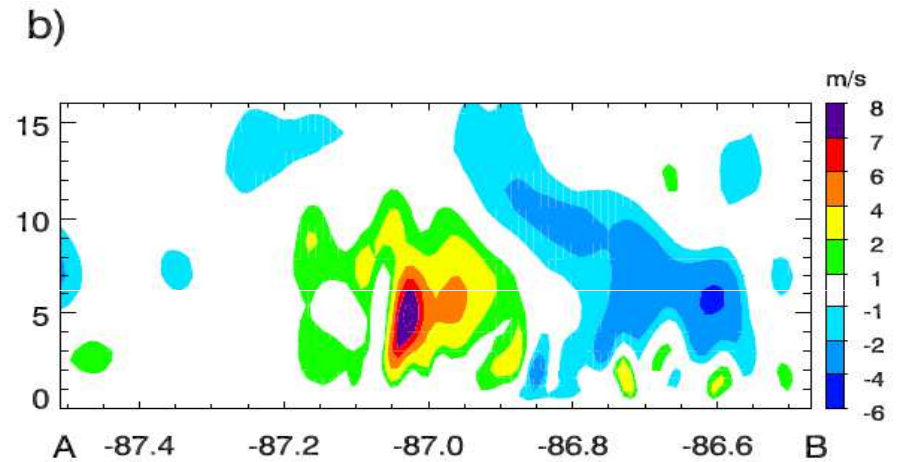
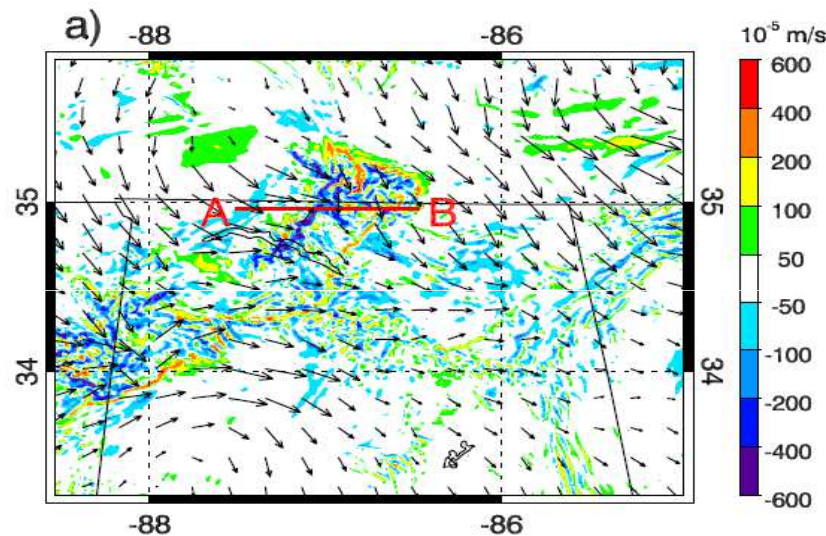
Black: Rain Water

Red: Cloud Water

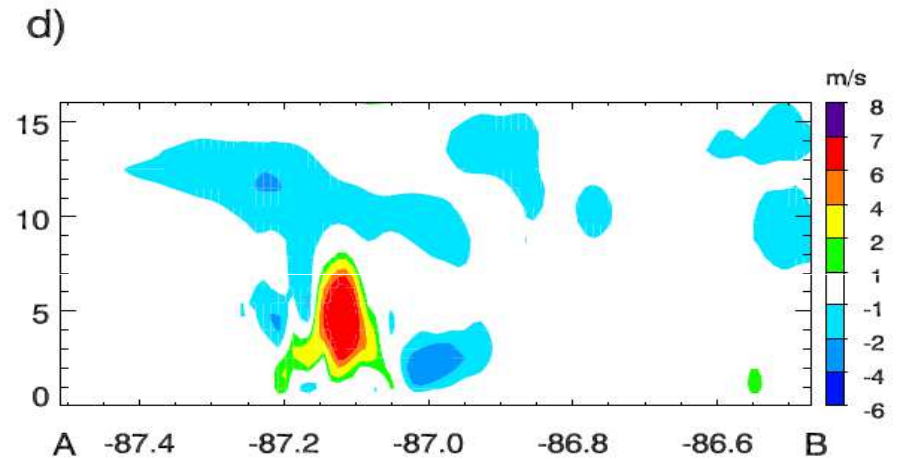
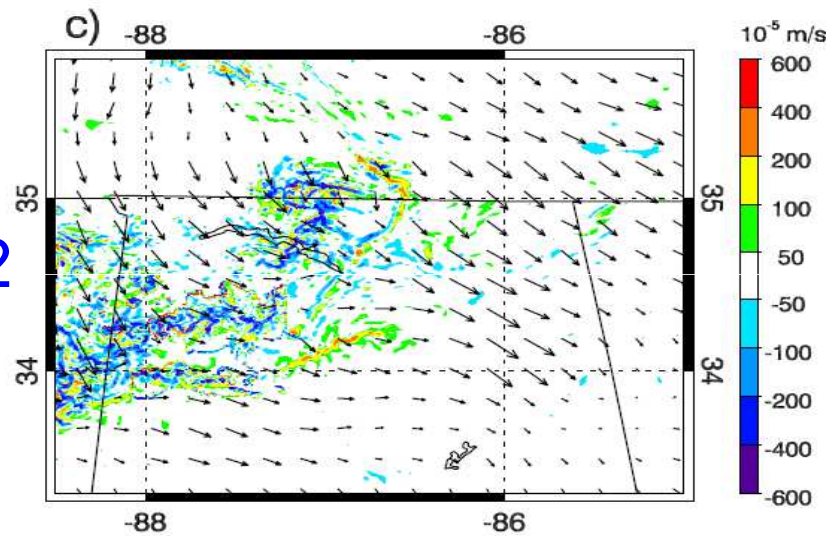
**Up to 15% difference
in rain water content;
OPER2 produces
more rain.**

Low Level Convergence & Vertical Velocity

OPER1

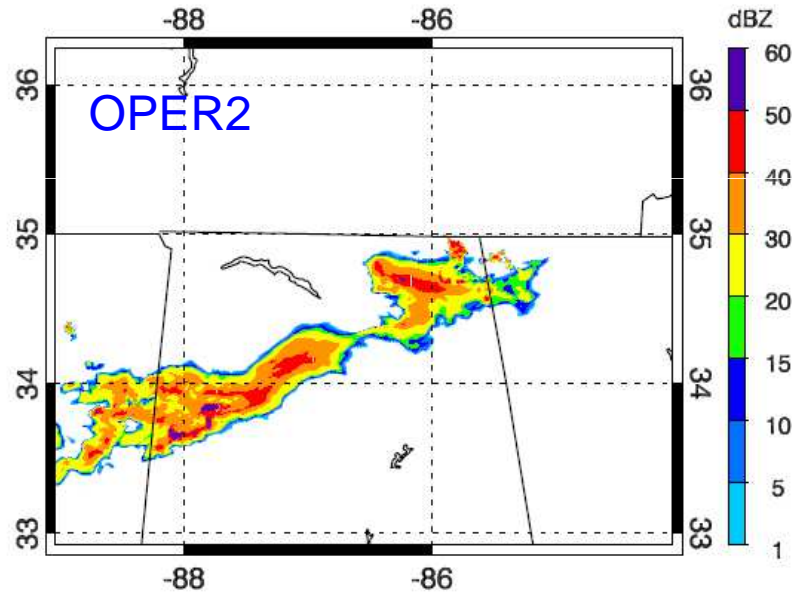
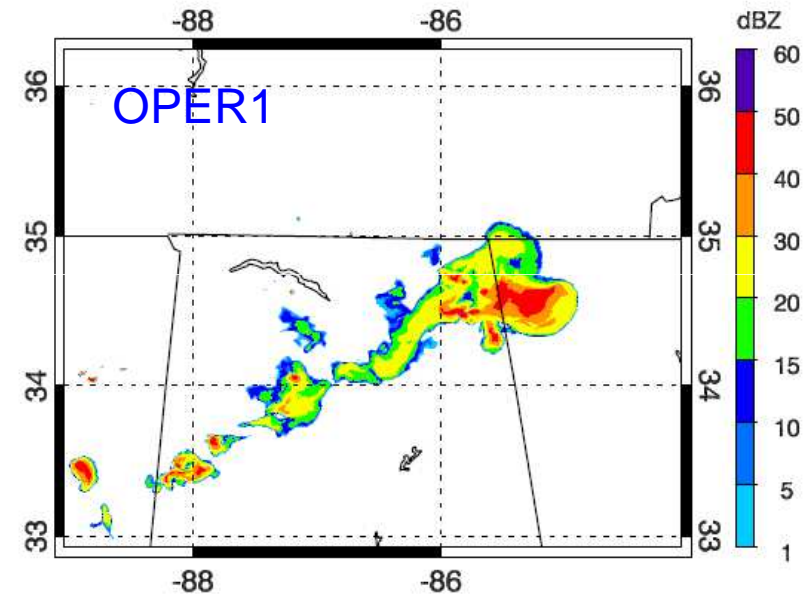
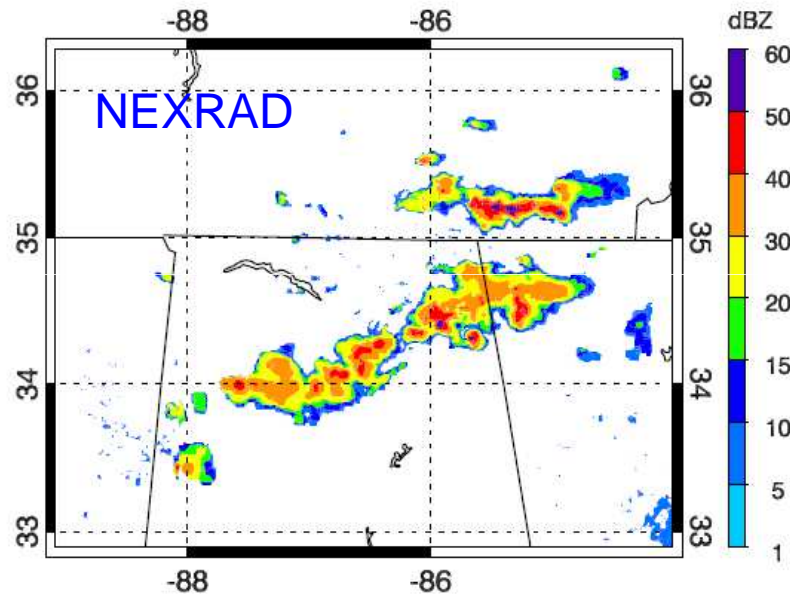


OPER2



OPER2: stronger updraft and low level convergence

Forecast Validation 2200 UTC

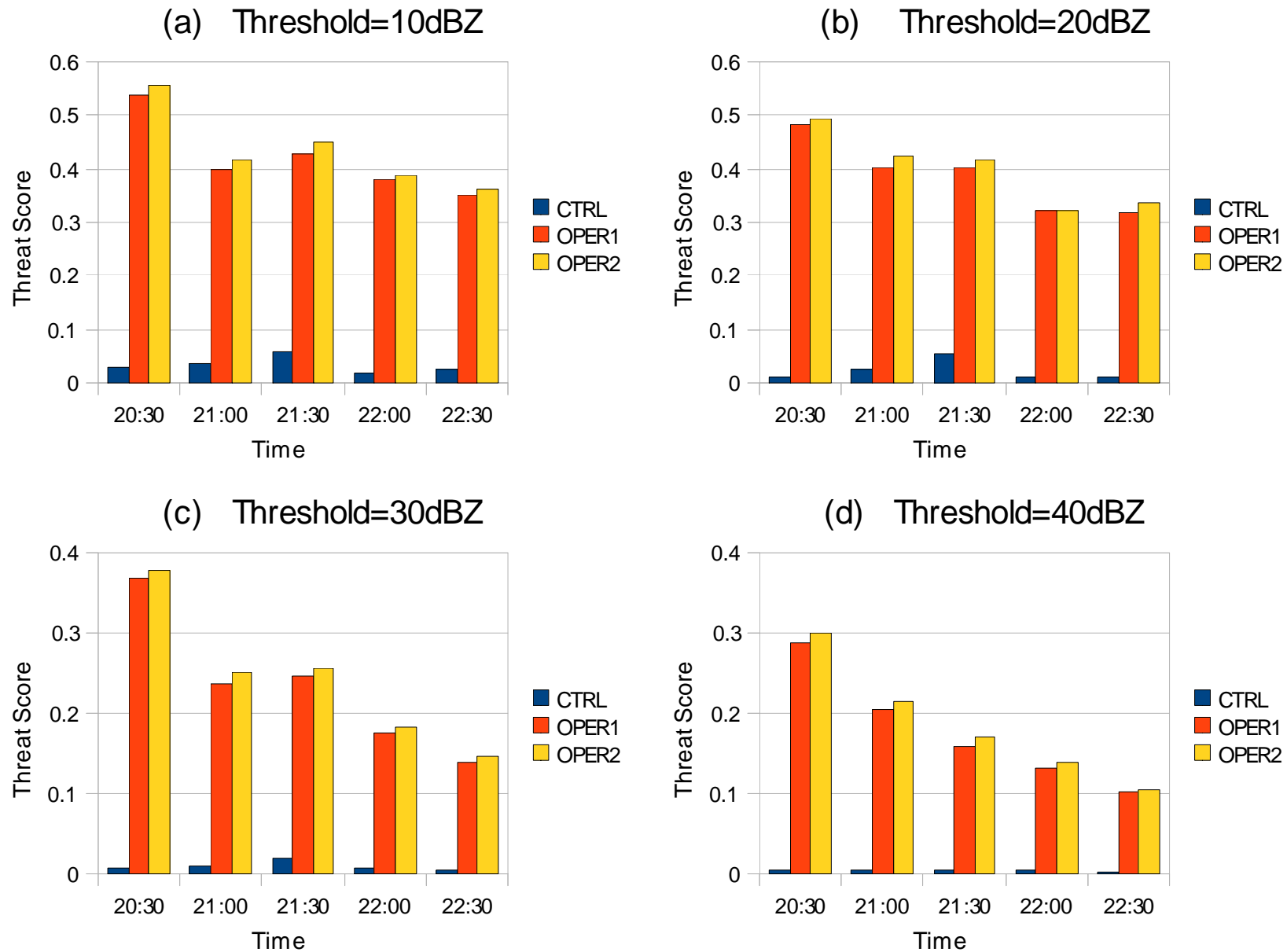


Location: similar

Storm Structure: quite different

Quicker dissipation in OPER1

Forecast Validation



OPER2: Slightly higher Threat Scores at all times
Threat Score difference of OPER2–OPER1 < 0.06

Dual-Pol Radar Data Assimilation Work

- The C-band dual-pol radar variables, Z_H , Z_{DR} , K_{DP} and VR data have been successfully assimilated with the WRF 3DVAR system.
- K_{DP} and Z_{DR} data assimilation is superior to Z_H and Z_{DR} , and Z_H -only data assimilation, in the initialization of the simulated convective storm with warm rain radar operators.
- OPER2 outperforms OPER1 for K_{DP} and Z_{DR} assimilation.

$$q_r = 2.32 \times K_{DP}^{0.83} \times \mathfrak{S}_{DR}^{-1.11}$$

On-going work:

1. Toward S-band dual-pol radar data assimilation;
2. Additional case studies, ice-phased processes in 3DVAR;
3. Complete information content & forward operators ([below](#));
4. Utilization of additional dual-pol variables in the characterization of ice microphysics.

MCMC-Based Analysis

Dual-Pol Radar Ice Information Content

Markov chain Monte Carlo (MCMC)

Objectives:

- Assess information content in observations
- Determine whether ice content and particle size distribution can be uniquely determined

Procedure:

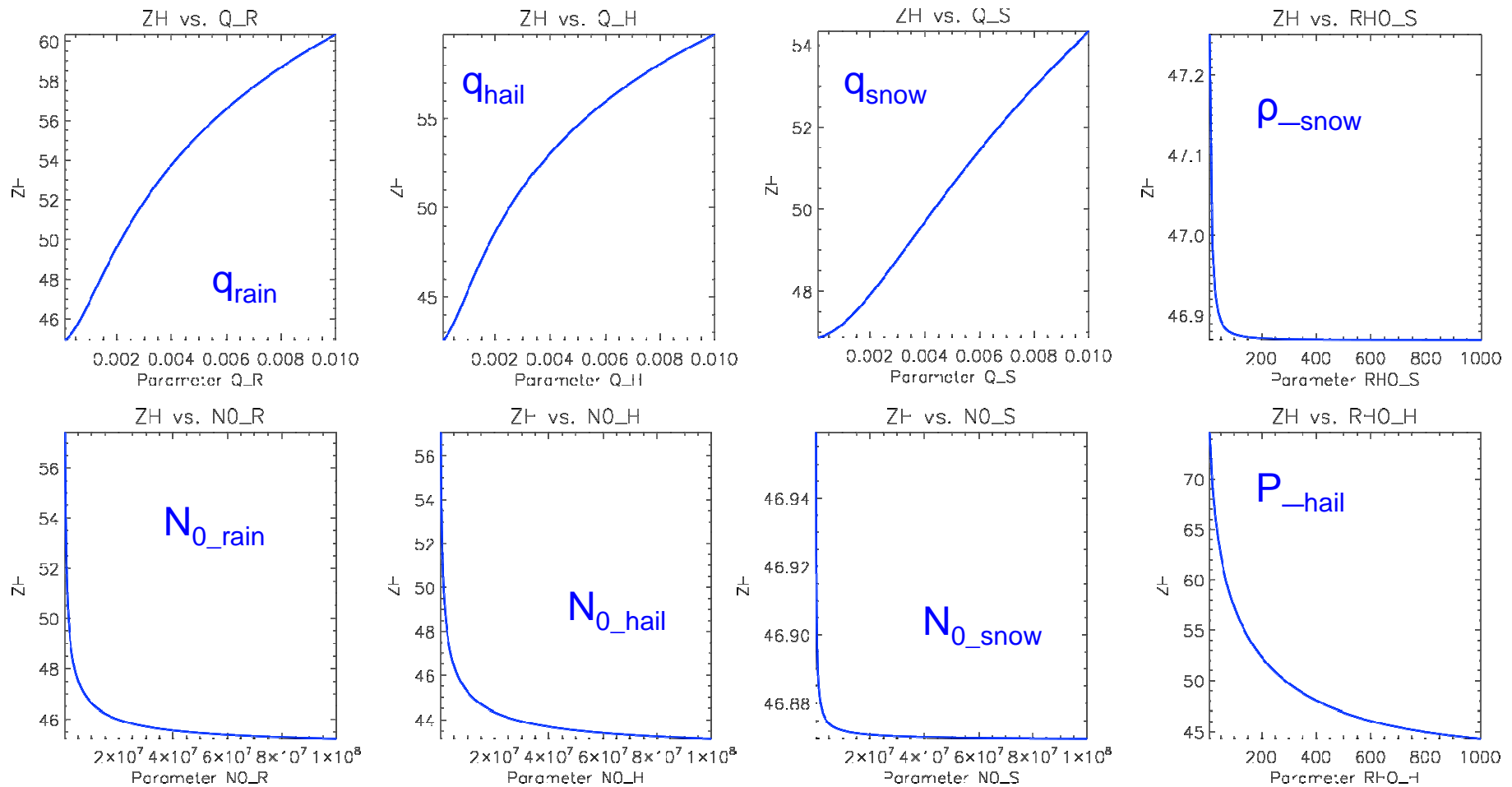
- Map (response) functional relationship between control variables and dual-pol forward observations
- Use a Bayesian probability sampling algorithm (MCMC) to produce posterior PDFs of control variables given *simulated observations* and assess information content and uniqueness

Data:

- WRF output at 1800 UTC 23 June 2008
- Simulated dual-polarimetric observations from WRF output
- MCMC-based computation of control variables PDFs
- Use select grid boxes only, that contain significant ice hydrometeors

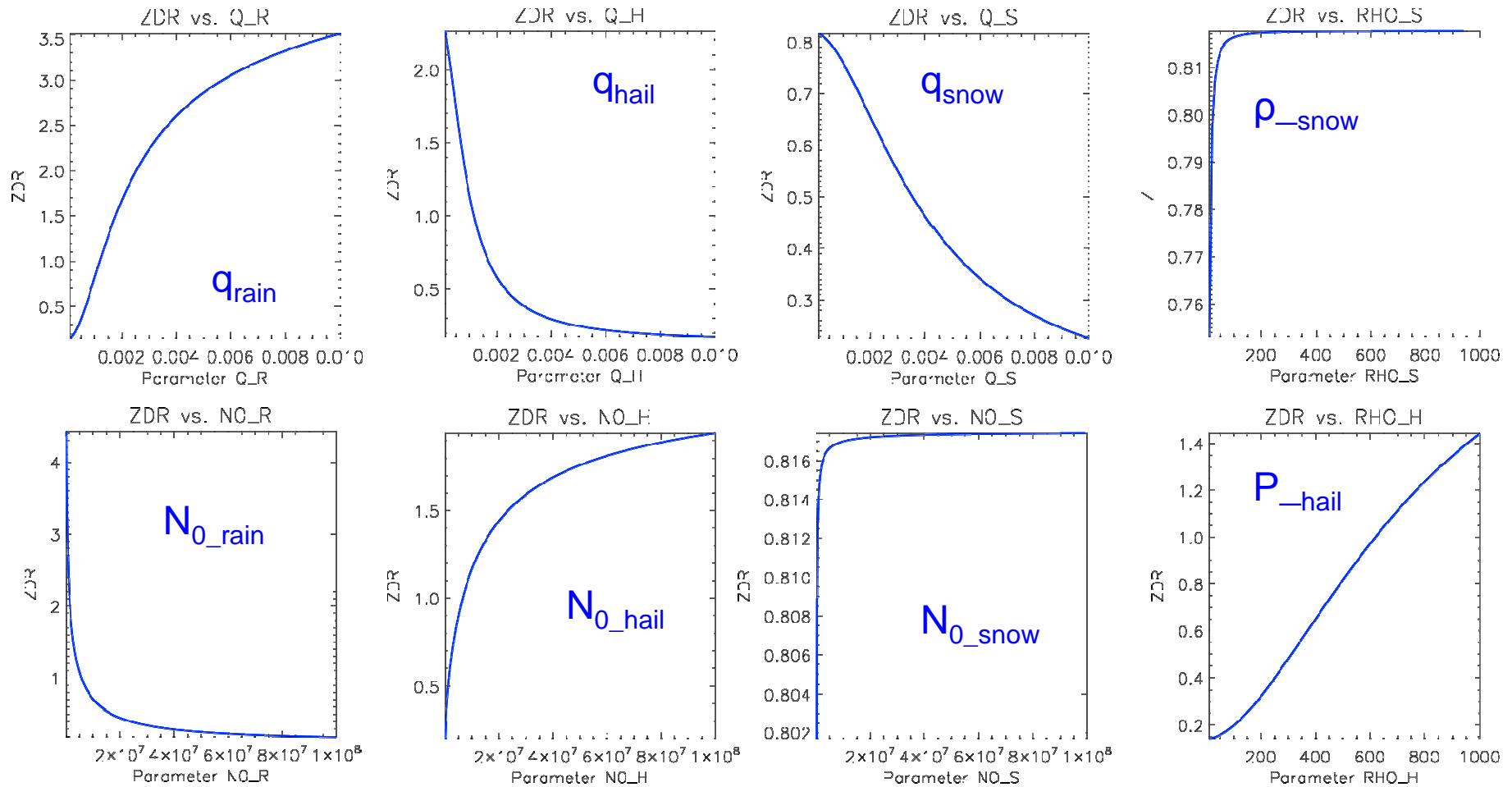
Response Functions

- Vary mixing ratio and particle size distribution slope intercept over a range of values, and compute forward modelled Z_H .



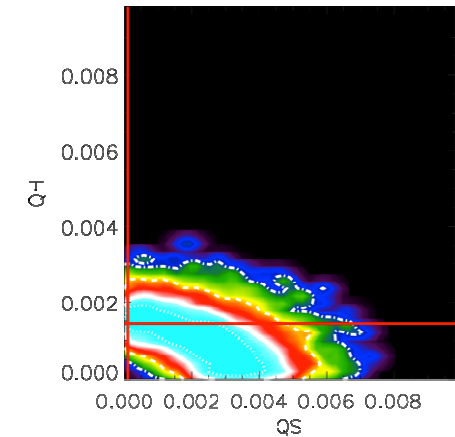
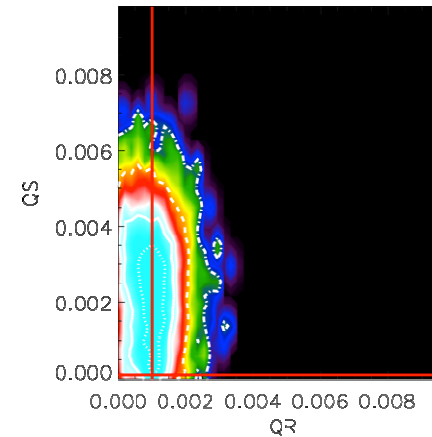
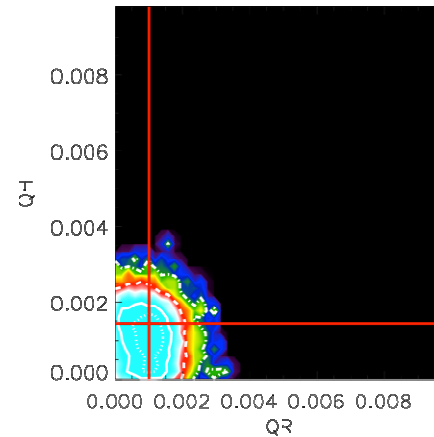
Response Functions

- Vary mixing ratio and particle size distribution slope intercept over a range of values, and compute forward modelled Z_{DR} .

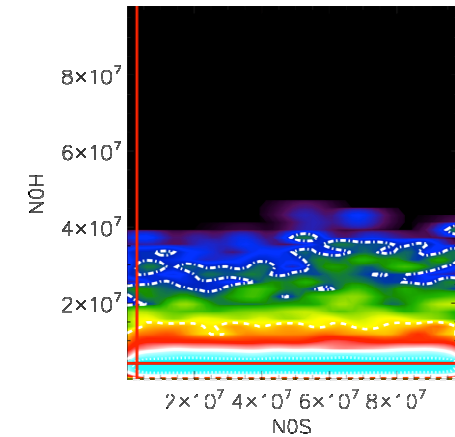
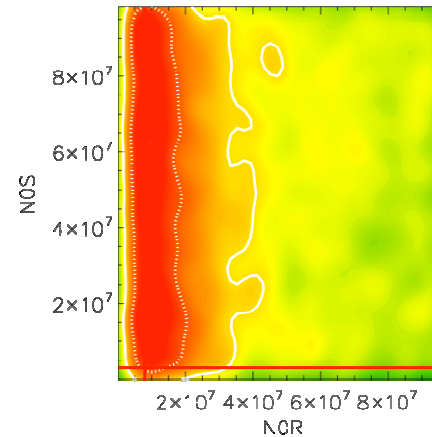
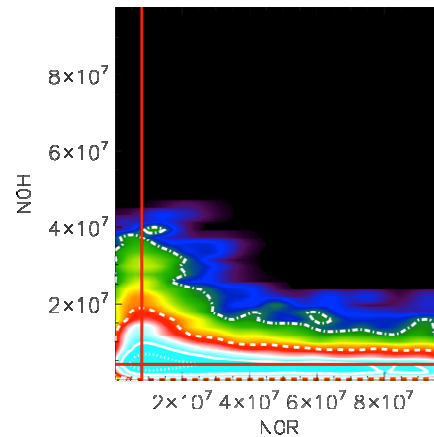


Posterior PDFs

Vary mixing ratios,
hold all others
constant



Vary particle size
distribution slope
intercept, hold all
others constant

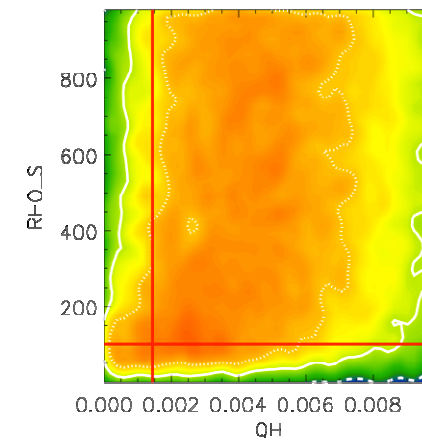
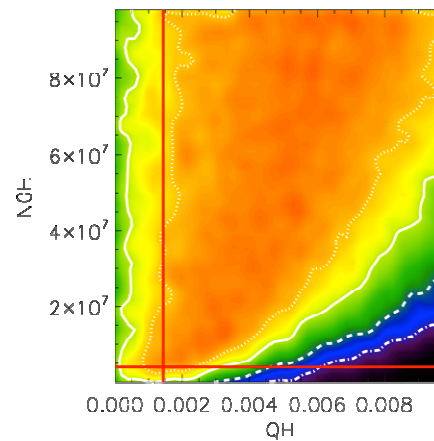
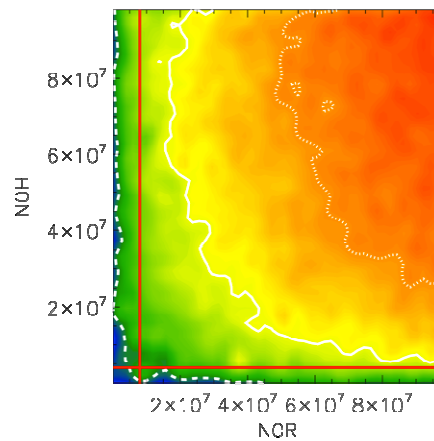
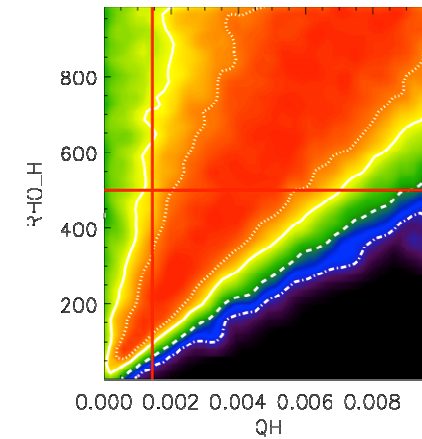
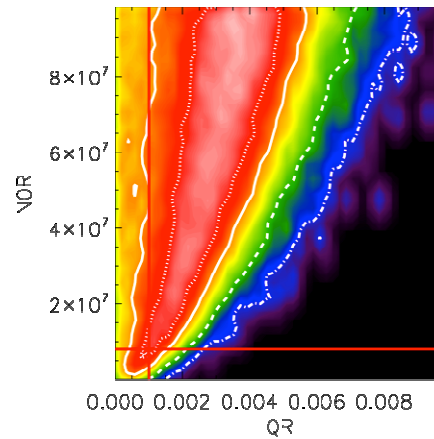
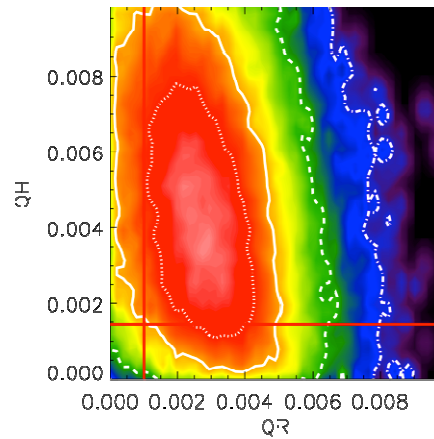


Probability Density Functions (PDF) are color-filled contours of the posterior 2D marginal probability density for each pair of variables. Only pairs that exhibited significant and/or interesting relationships are shown.

The “true” value of each control variable is plotted in the **red cross-hairs**. The **white contours** are of probability mass with dash-dot = 99.7%, dashed = 95%, solid = 68.3%, and dotted at center 37%, which correspond approximately to 3, 2, 1, and 0.5 standard deviations around the mode of the PDF.

Posterior PDFs

Allow all mixing ratios, PSD slope intercepts, and snow and graupel density to vary



Some Description

The response functions map the functional relationships between changes in each control variable and the dual-pol forward observations. These are effectively the sensitivities, and can be thought of as the Jacobian matrix of partial derivatives of the forward state with respect to the control variables [mixing ratios and particle size distribution (PSD) parameters].

The PDFs are a solution if we assimilated dual-polarimetric observations for the grid box of interest only.

Understanding so far...

If we only try to constrain PSD parameters, we get a unique solution for rain and hail, but not for snow.

The same is true for the mixing ratios – if we only try to constrain q_r , q_s , and q_h/q_g , then we obtain q_r and q_h , but not q_s .

If we try to use the dual polarimetric observations to constrain both mixing ratios and PSD parameters, there simply isn't enough information.

There exists 1-2 unique pieces of information between Z_H , Z_V , and Z_{DR} , which is not enough to constrain more than 2 unknowns.

More information is gained by bringing in additional dual polarimetric variables.

Preliminary Conclusions and Future Works

- Dual-pol Z_H , Z_V , and Z_{DR} can uniquely constrain either mixing ratio or particle size distribution of rain and hail/graupel, *but not both*.
- Clear functional relationship evident between q_r/N_{0r} , q_h/N_{0h} , and q_h/ρ_h
- Snow not well constrained by dual-pol observations
 - Z_{DR} and Z_H response function showed little sensitivity to changes in snow variables
 - Snow amount was 0.1 times q_r and q_h for the WRF grid box in this experiment

Questions:

- How might response function change with changes in the state, e.g., temperature, water vapor, pressure, and cloud amount; How, in turn, would the posterior PDFs change?
- Would assimilation of K_{dp} and ρ_{hv} serve to produce unique values of both cloud mass and particle size distribution?

Follow-on Work:

Re-run experiments for additional model grid boxes: (1) containing comparable (and small ~ 0.1 g/kg) amounts of snow, graupel, and rain, (2) containing snow and graupel only, (3) containing snow only. Include additional dual polarimetric variables (ρ_{HV}).

