Variational retrieval of warm rain from GMI

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CSU 1DVAR

Developed at Colorado State University, Fort Collins CO [*Duncan and Kummerow 2016]*

- 1DVAR retrieval applicable to microwave imagers
  – Retrieve water vapor, cloud water, wind speed, and SST over ocean
  – Validation for GMI and AMSR2 rivals that of Wentz products
- Non-diagonal observation error covariances
- 13 channel, 6 variable retrieval (3 PCs of water vapor)
- Forward model uses CRTM with FASTEM6

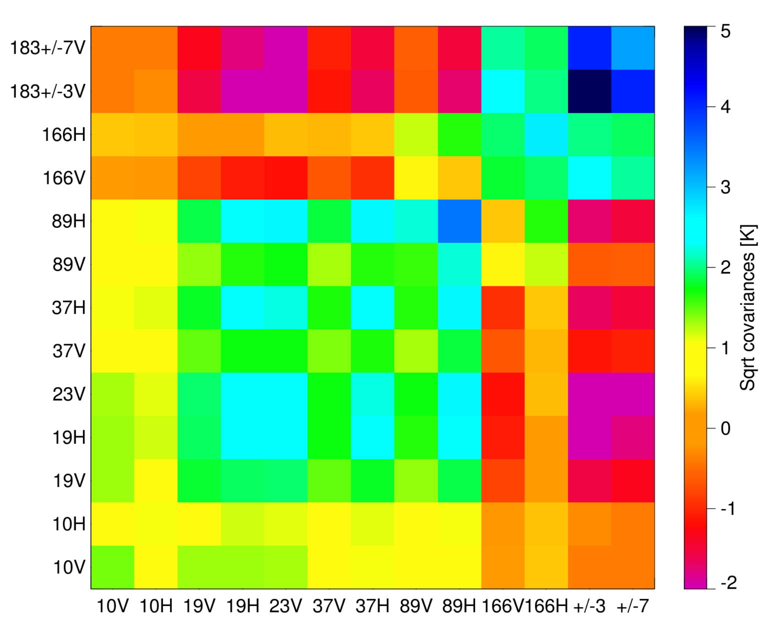
CSU 1DVAR

VAR cost function

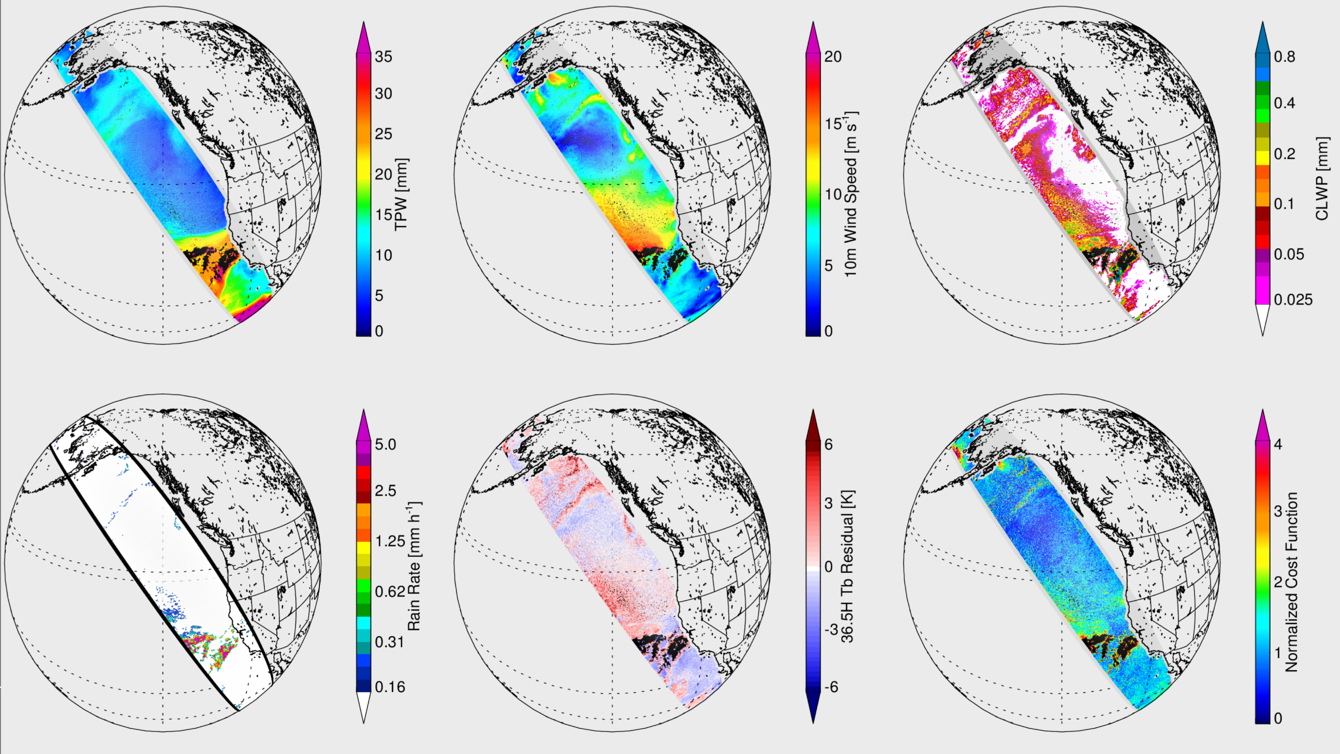
$$\Phi = (\mathbf{x}-\mathbf{x}_a)^T \mathbf{S}_a^{-1} (\mathbf{x}-\mathbf{x}_a) + [\mathbf{y}-f(\mathbf{x},\mathbf{b})]^T \mathbf{S}_y^{-1} [\mathbf{y}-f(\mathbf{x},\mathbf{b})]$$

'Full' observation error covariances

Important for correlated forward model errors



CSU 1DVAR



GMI

Nov 30th 2014

[Duncan and Kummerow 2016]

Extend to warm rain

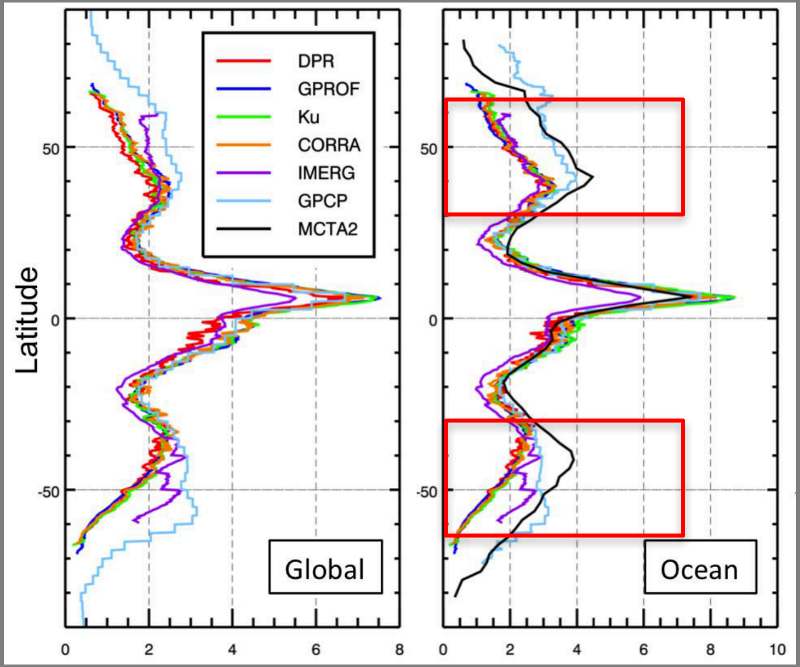
What are the challenges we need to overcome?

1. **Partition columnar liquid**
2. **Hydrometeor profiles (vertical information)**
3. **Treatment of drop size distributions (DSDs)**

Why care about warm rain? Why variational retrieval?

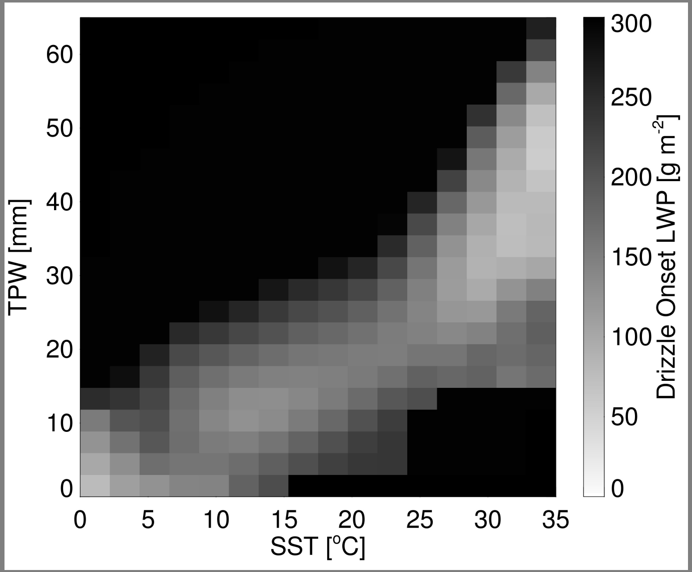
Extend to warm rain

- GPM and A-Train disagree at high latitudes
- GMI is more sensitive to drizzle than DPR
- Warm rain is ~35% of oceanic rain occurrence and 19% of accumulation [*Chen et al. 2011*]
- If GMI retrieval is tied to DPR (like GPROF, CORRA), it can waste valuable signal in warm rain
- Properly treated, VAR maximizes signal to noise of warm rain—better than Bayesian or DA schemes



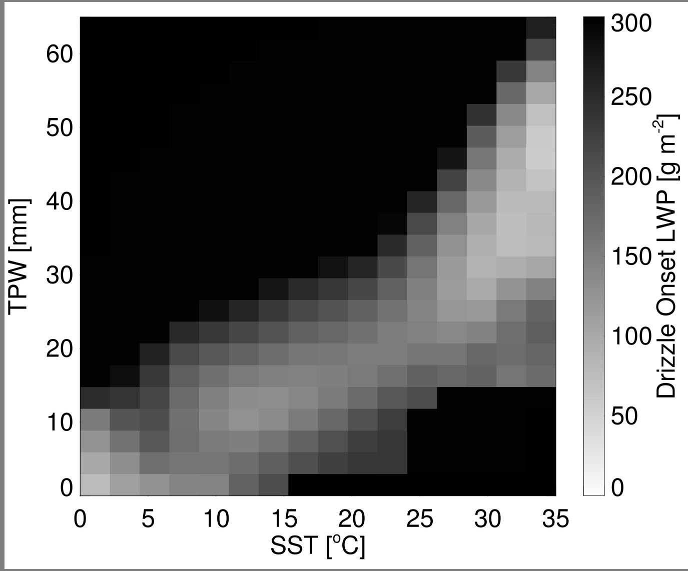
[*Skofronick-Jackson et al. 2017*]

Extend to warm rain



- Match up CloudSat precipitation occurrence data, separated by WV/SST regime, to calculate drizzle onset LWP values
- These are in line with *Wentz and Spencer 1998*, *Lebsock and L'Ecuyer 2011*, *Chen et al. 2011*— around 180g/m^2 but with regime dependence

Extend to warm rain



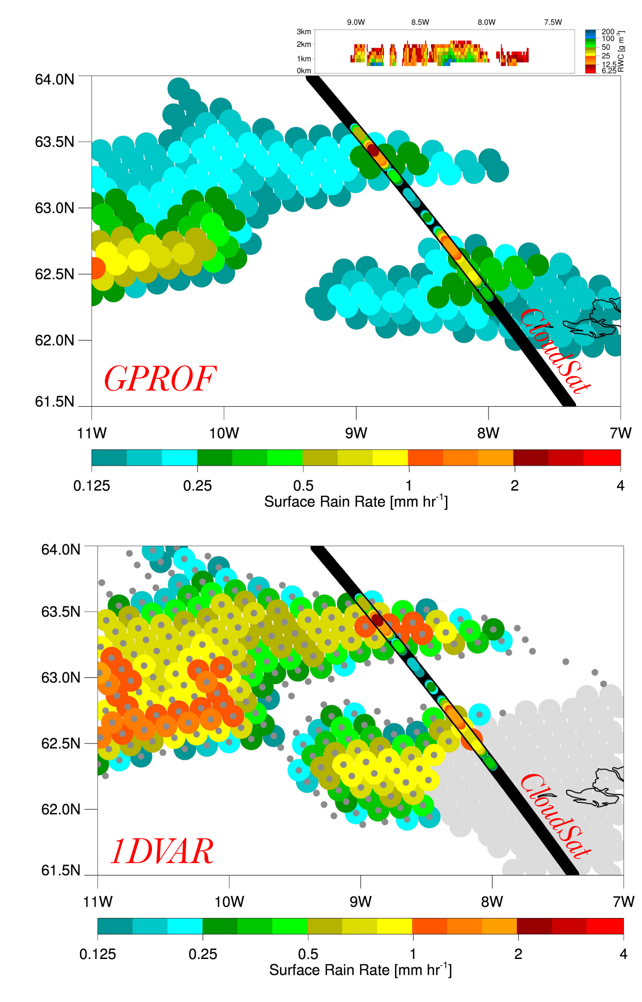
Simple case (not true VAR precip retrieval):

AMSR2/CloudSat in N. Atlantic

Regression-based rain rate after standard retrieval converges

$$RWP = LWP - LWP_{driz}$$

$$RR = 5*RWP^{1.1}$$



[Duncan et al. 2017]

Extend to warm rain

For true VAR precip retrieval we still need:

2. *vertical information to run the forward model*
3. *treatment of DSD variability*

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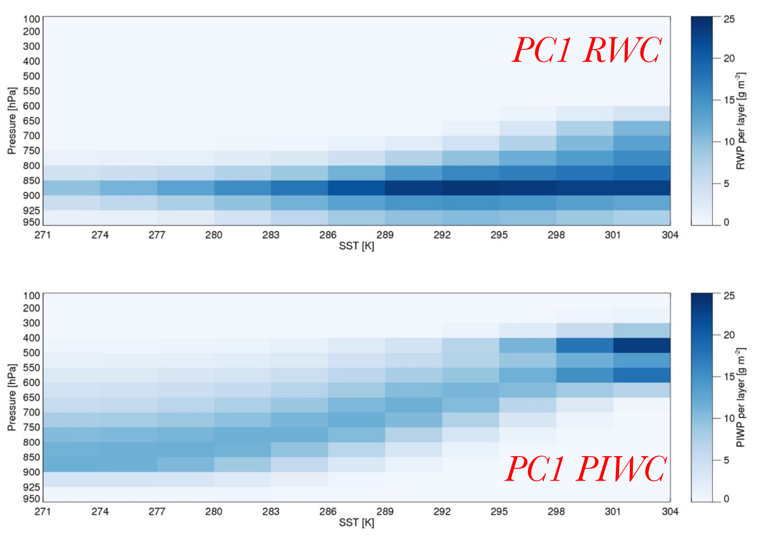
Take profile data from CloudSat 2C-Rain-Profile product [*Lebsock and L'Ecuyer 2011*]

Reduce dimensionality using principal component analysis (PCA)



Extend to warm rain

For true VAR precip retrieval we still need:

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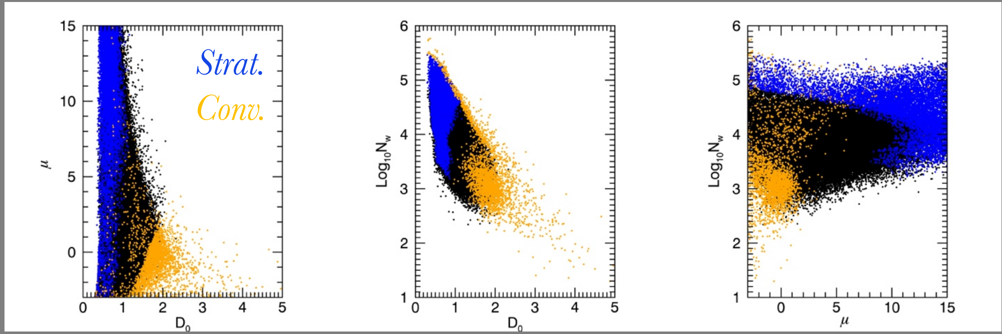
3. *treatment of DSD variability*

Need to choose realistic/physical drop distribution for running forward model and calculating RR.

Also need to account for forward model error incurred by assuming a DSD!

Disdrometer data from LPVEX & OLYMPEX

Separate DSD observations via PCA analysis to approximate convective/stratiform classes



$$N(D) = N_w f(\mu)\left(\frac{D}{D_m}\right)^{\mu} e^{-(4+\mu)D/D_m}$$

From [*Dolan et al. 2016*]

Extend to warm rain

For true VAR precip retrieval we still need:

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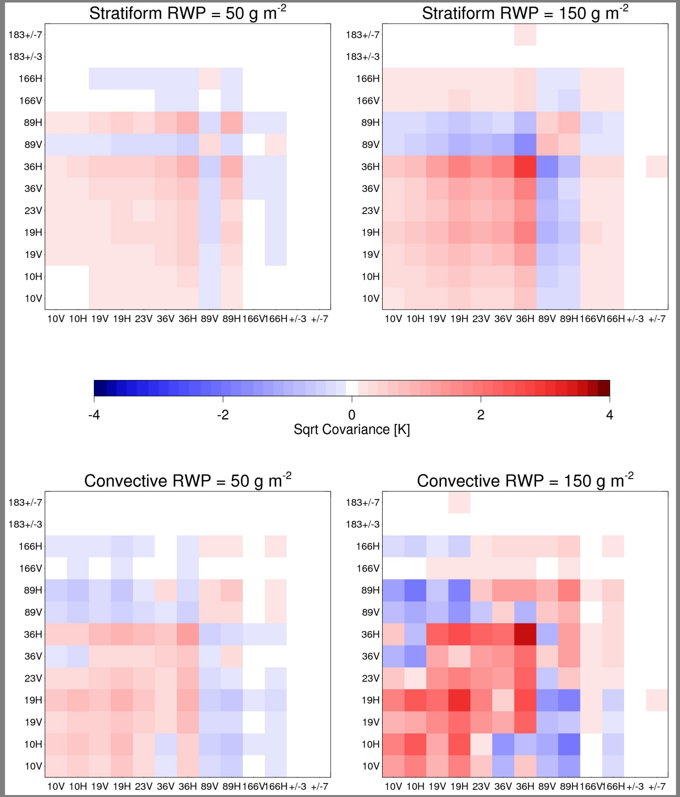
3. *treatment of DSD variability*

Run DSD parameters through CRTM to calculate errors from using an a priori DSD:

$$\sigma_{conv}(\nu) = \mathrm{stddev}(T_B[\nu, DSD_{conv}] - T_B[\nu, DSD_{actual}])$$

Observation errors are *scene-dependent* and vary during iteration!



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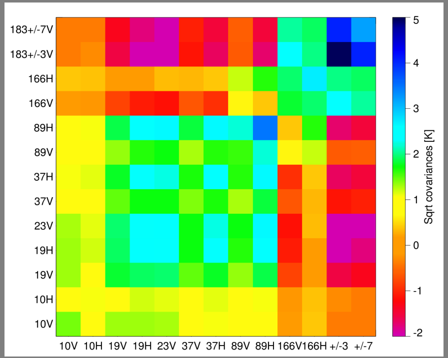

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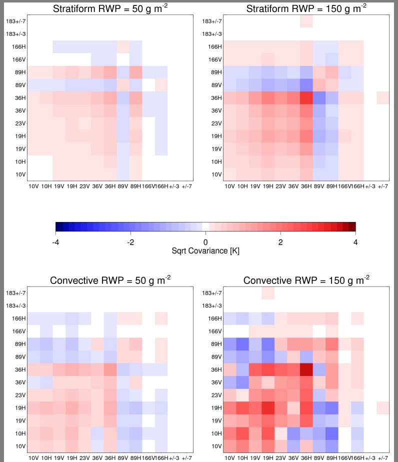

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$$S_y(\mathit{RWP}, \mathit{stra}) = S_{y,\text{non-raining}} + S_{y,\text{stra}}(\mathit{RWP})$$

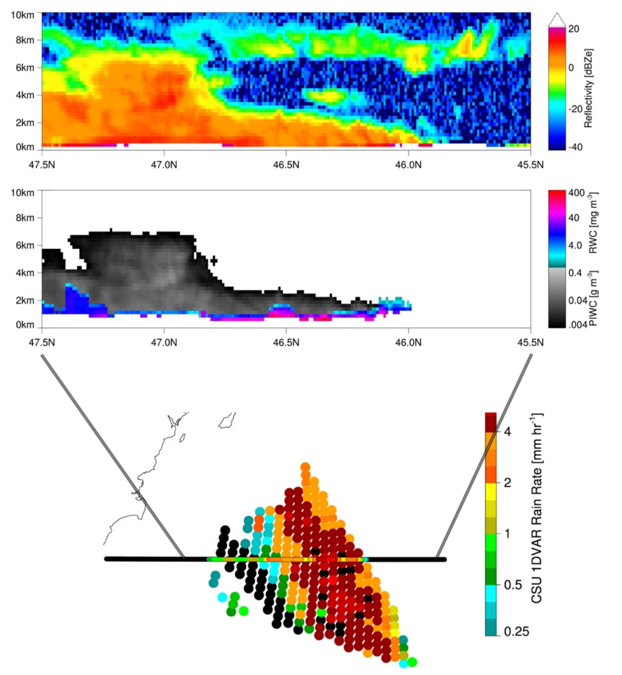
In practice:

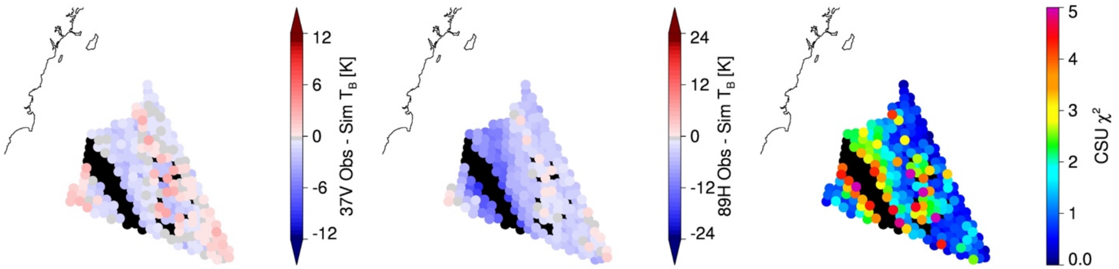
Non-raining ➡ Stratiform ➡ Convective

Results

Co-location with CloudSat shows promise but also shortcomings

- *1DVAR matches CloudSat retrieval magnitudes better than GPROF*
- *Areas of non-warm rain fail to converge*
- *Simulated vs. observed GMI T_B demonstrates useful information gained (e.g. for DA applications)*





Results

Performance relative to DPR

- *Footprint averaging of DPR NS to GMI at 23GHz FOV*
- *Warm season summer only—DJF (30˚S+), JJA (30˚N+)*
- *Co-located percentage of precipitation beyond threshold rain rates*

	Cutoff [mm hr^{-1}]	DPR rain	1DVAR rain	DPR only	1DVAR only	Either	1DVAR missed
Southern Hemisphere	0.20	5.7%	13.9%	4.2%	10.0%	18.1%	0.4%
	1.00	1.5%	7.3%	1.3%	4.9%	8.6%	0.0%
Northern Hemisphere	0.20	7.9%	12.5%	3.7%	6.1%	16.3%	0.3%
	1.00	1.9%	6.6%	1.7%	2.3%	8.3%	0.0%

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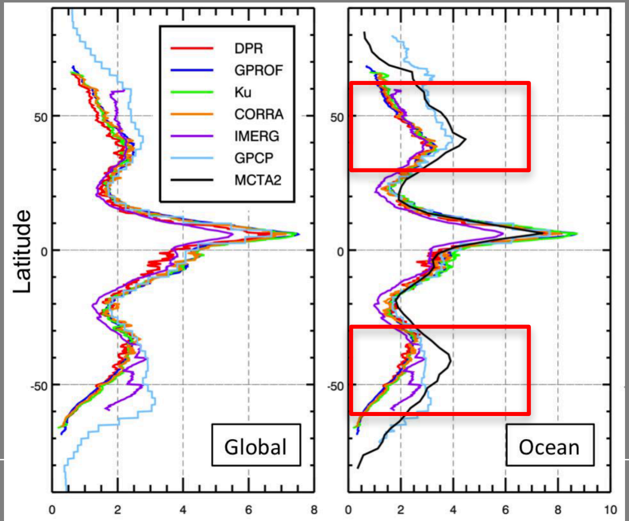

Conclusions

- 1DVAR sees significantly more light rain than DPR—
  some is an overestimate, some is physical
- VAR is useful for rain detection but only for certain conditions, and quantification is problematic
- Comparisons against space- and ground-based radars show reasonable performance when forward model is valid
- Method is applicable to other latitudes (given DSD data)
- However, beyond warm rain VAR is inadvisable for GMI precip retrieval—
  some combination of Bayesian/VAR seems best for now

References

- Chen, R., Z. Li, R. Kuligowski, R. Ferraro, and F. Weng (2011), A study of warm rain detection using A-Train satellite data, *Geophys. Res. Lett.*, *38*, L04804, doi:10.1029/2010GL046217.
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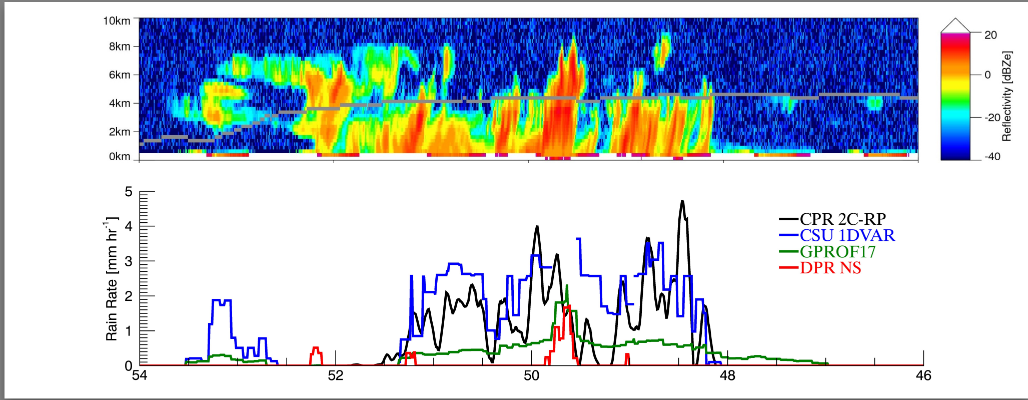
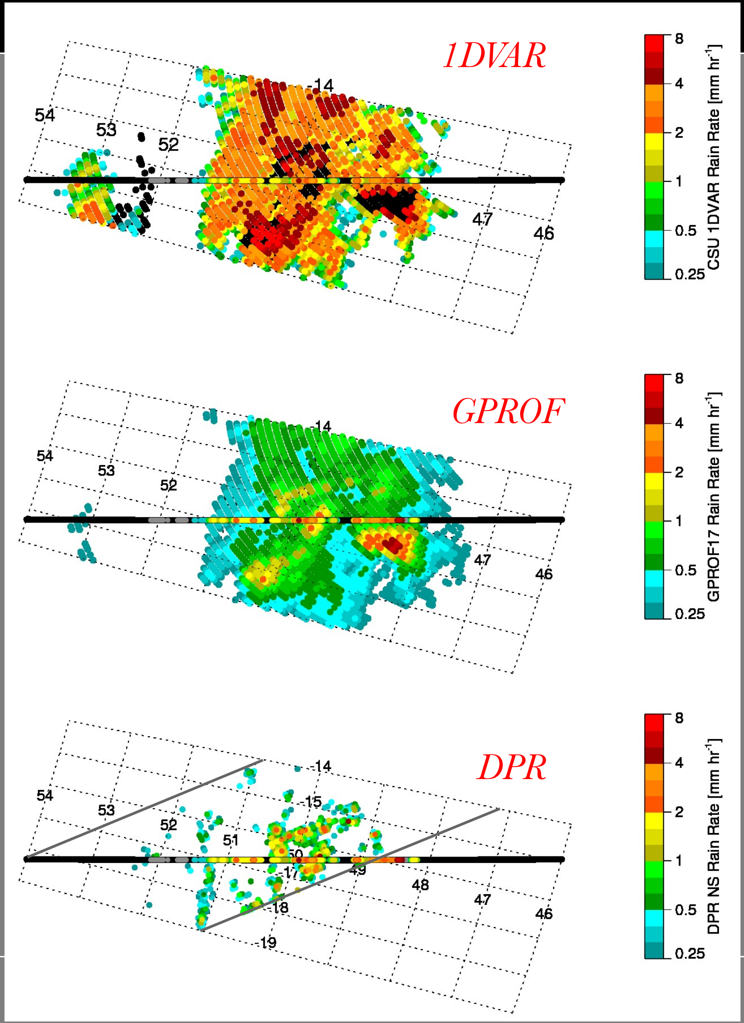
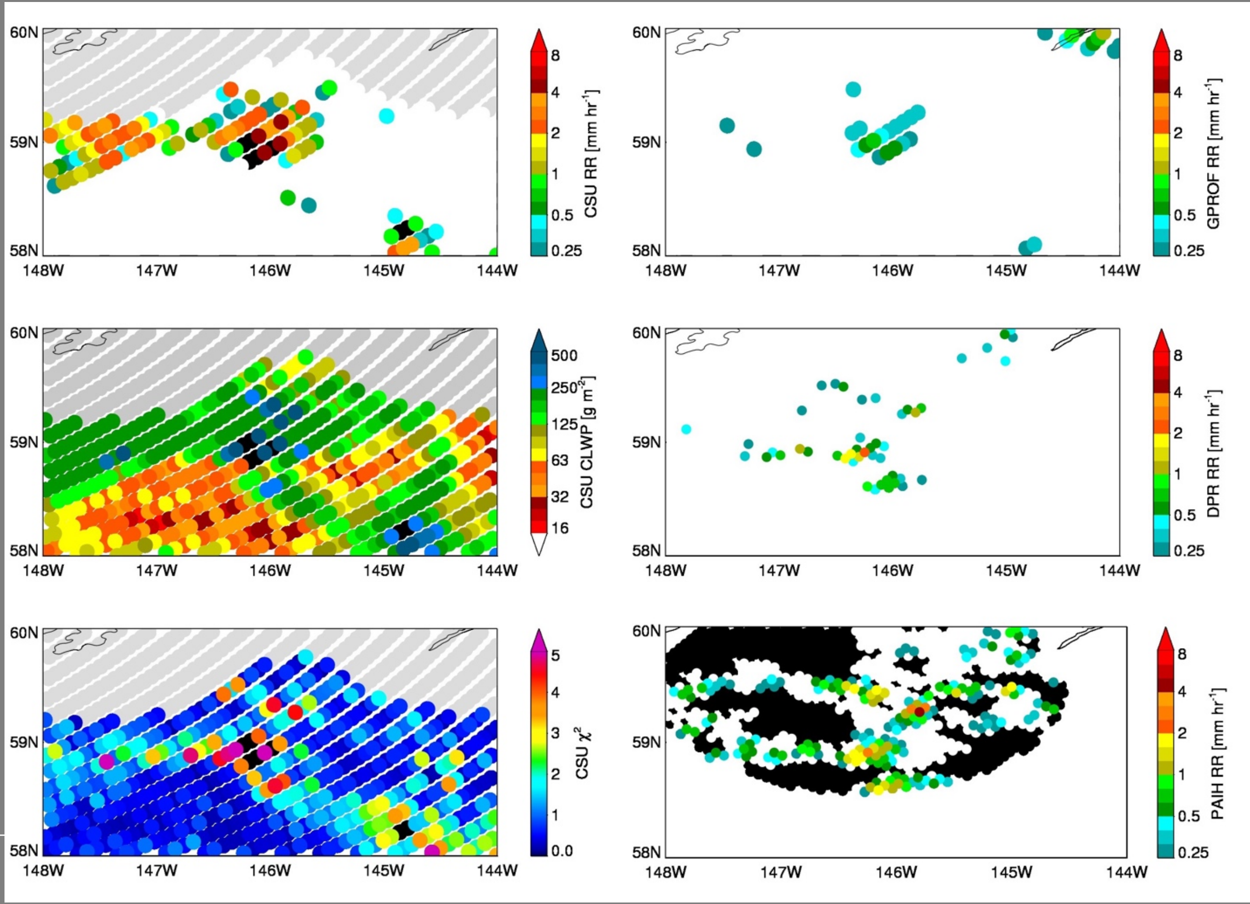
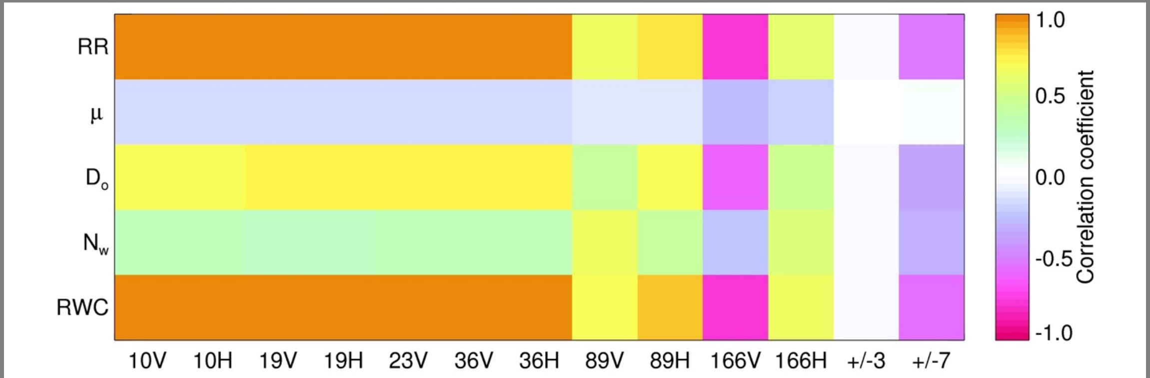
Backup slides


10km
8km
6km
4km
2km
0km
20
0
-20
-40
Reflectivity [dBZe]
Rain Rate [mm hr-1]
CPR 2C-RP
CSU 1DVAR
GPROF17
DPR NS
54
52
50
48
46


1DVAR
CSU 1DVAR Rain Rate [mm hr-1]
GPROF
GPROF17 Rain Rate [mm hr-1]
DPR
DPR NS Rain Rate [mm hr-1]
8
4
2
1
0.5
0.25


60N
59N
58N
148W
147W
146W
145W
144W
CSU RR [mm hr^{-1}]
8
4
2
1
0.5
0.25
GPROF RR [mm hr^{-1}]
CSU CLWP [g m^{-2}]
500
250
125
63
32
16
DPR RR [mm hr^{-1}]
CSU χ^2
5
4
3
2
1
0.0
PAIH RR [mm hr^{-1}]

Stratiform



Convective