



Variational Inversion of Hydrometeors Using Passive Microwave Sensors

-Application to AMSU/MHS, SSMIS and ATMS-

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Contents



Overview of MiRS Algorithm



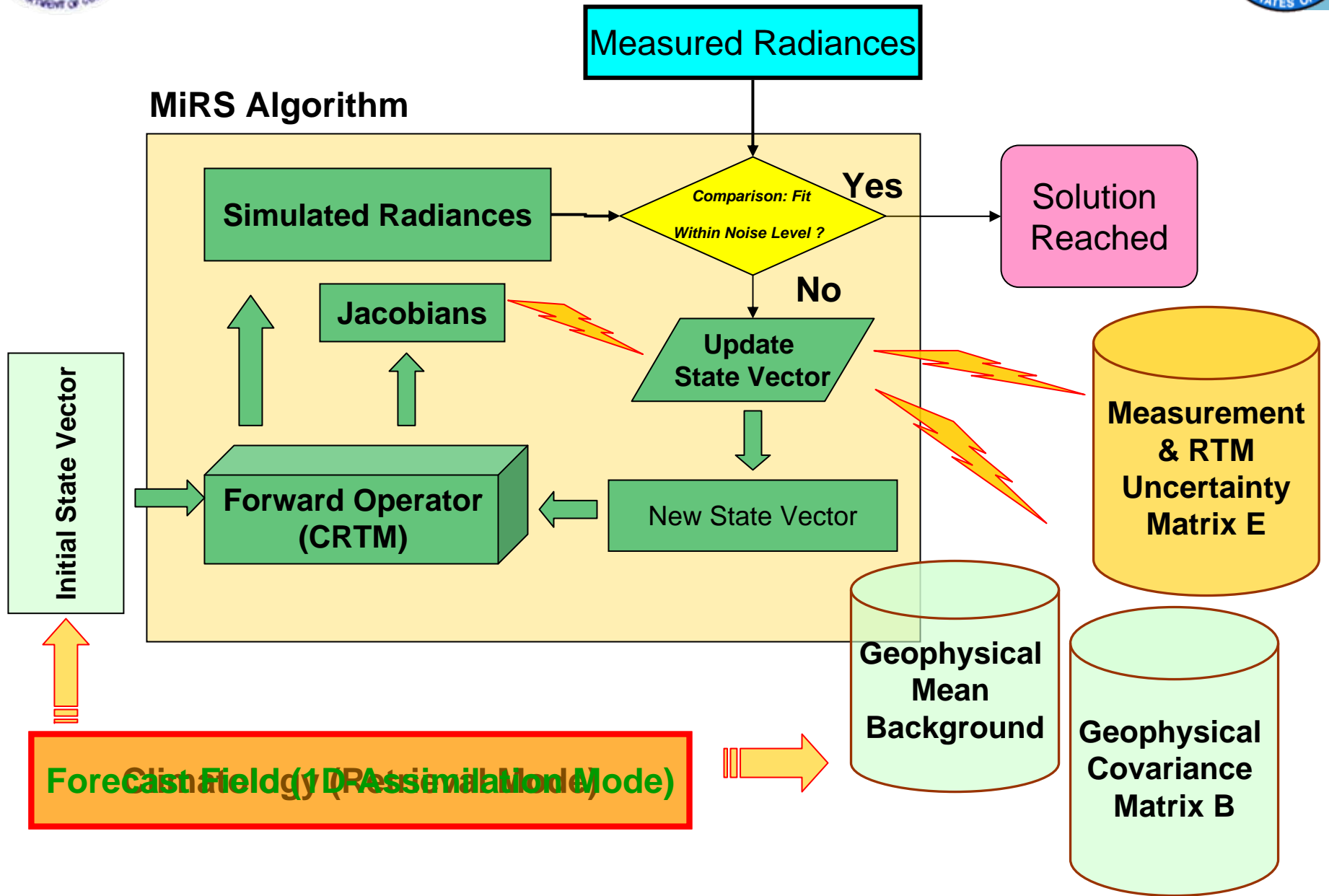
Concept of Cloud/Precip-clearing



Performance Assessment



Summary & Conclusion





Quality Control of MIRS Outputs



❖ Convergence Metric: ϕ^2

❖ Uncertainty matrix S :

$$S = B - B \times K^T \left(K \times B \times K^T + E \right)^{-1} \times K \times B$$

❖ Contribution Functions D : indicate amount of noise amplification happening for each parameter.

$$D = B \times K^T \left(K \times B \times K^T + E \right)^{-1} \times \left(Y(X) - K \times X_0 \right)$$

❖ Average kernel A :

$$A = D \times K$$

- If close to zero, retrieval coming essentially from background
- If close to unity, retrieval coming from radiances: No artifacts from background



Parameters are Retrieved Simultaneously



If X is the set of parameters that impact the radiances Y^m , and F the Fwd Operator



If $F(X)$ Does not Fit Y^m within Noise



X is not the solution

Necessary Condition (but not sufficient)

$F(X)$ Fits Y^m within Noise levels



X is a solution



X is the solution



All parameters are retrieved simultaneously to fit all radiances together

Suggests it is not recommended to use independent algorithms for different parameters, since they don't guarantee the fit to the radiances



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Sounding Retrieval:

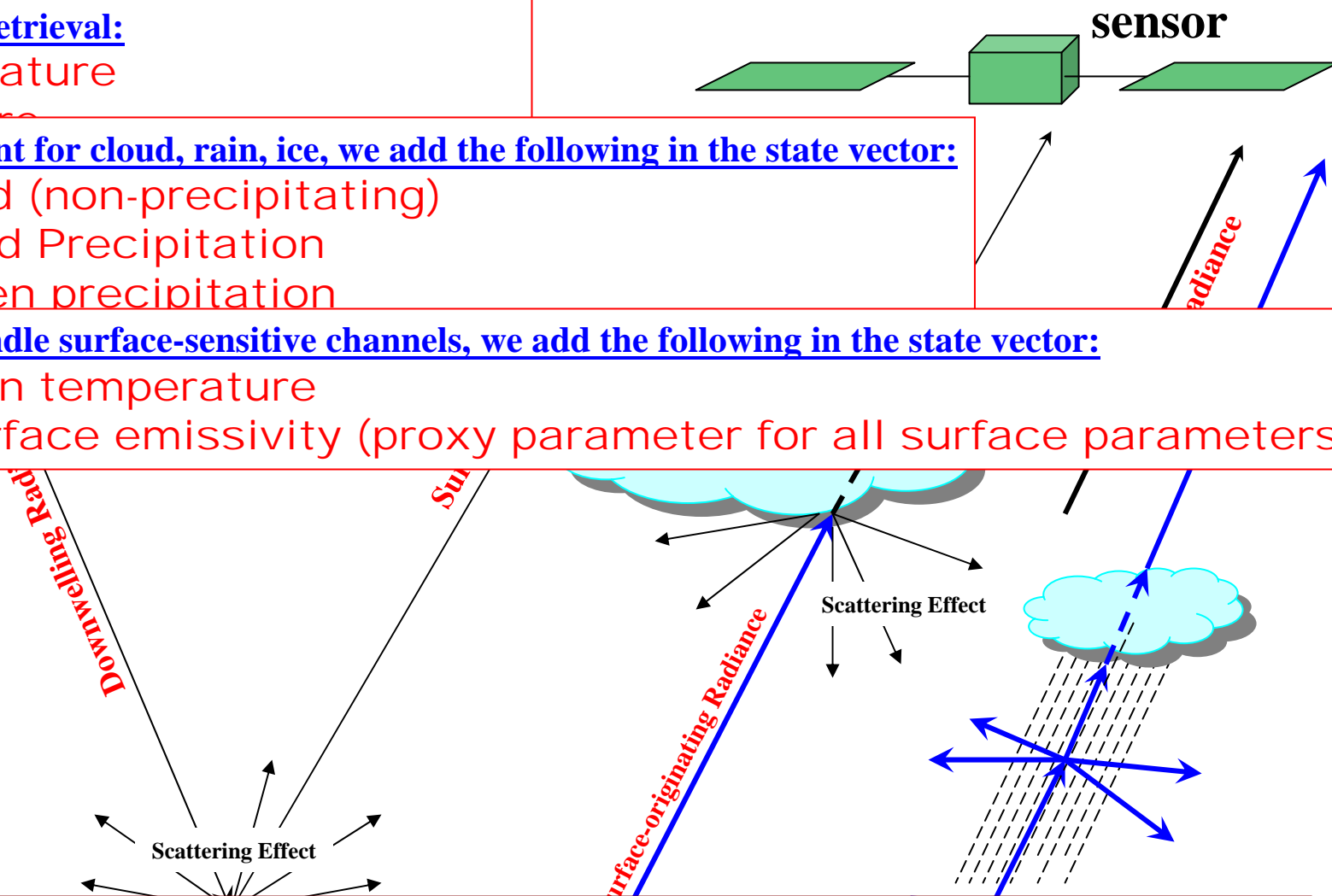
- Temperature
- Moisture

To account for cloud, rain, ice, we add the following in the state vector:

- Cloud (non-precipitating)
- Liquid Precipitation
- Frozen precipitation

To handle surface-sensitive channels, we add the following in the state vector:

- Skin temperature
- Surface emissivity (proxy parameter for all surface parameters)



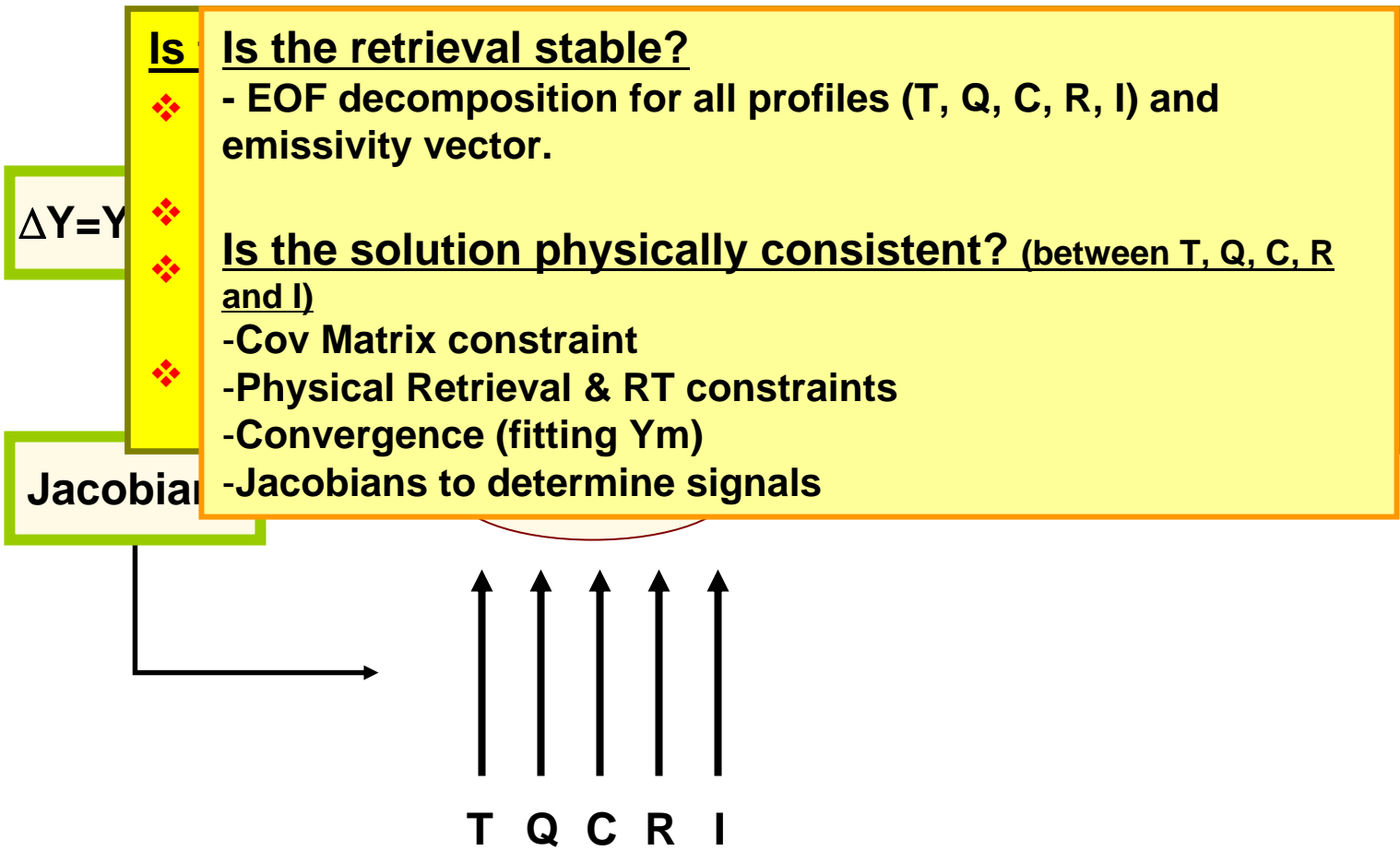
- ❖ Instead of guessing and then removing the impact of cloud and rain and ice on TBs (very hard), MiRS approach is to account for cloud, rain and ice within its state vector.
- ❖ It is highly non-linear way of using cloud/rain/ice-impacted radiances.



All-Weather: Cloud/Precip-Clearing



- ❖ Instead of guessing impact of cloud and rain and ice on TBs (very hard), MiRS approach is to account for cloud, rain and ice within its state vector.
- ❖ Advantages:
 - It is highly non-linear way of using cloud/rain/ice-impacted radiances
 - Does not rely on cloud or rain uniform distribution
 - Does not rely on cloud resolving models (added uncertainty, need to linearize, speed cost, etc)
- ❖ Disadvantage:
 - Results depend on assumptions made in RT (particle size, distribution, etc)
 - Greater reliance on a robust, valid covariance matrix (flow dependent matrix becomes necessary: see poster by K. Garrett).



Solution-Reaching: Convergence

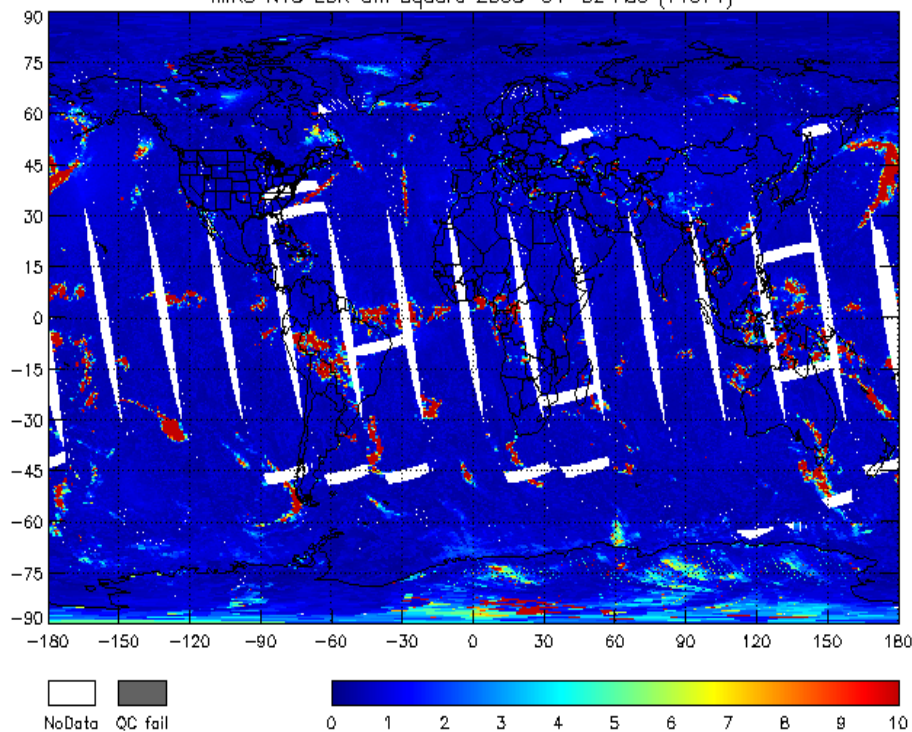
- ❖ Convergence is reached everywhere: all surfaces, all weather conditions including precipitating, icy conditions
- ❖ A radiometric solution (whole state vector) is found even when precip/ice present. With CRTM physical constraints.

$$\phi^2 = \left(Y^m - Y(X) \right)^T \times E^{-1} \times \left(Y^m - Y(X) \right)$$

Previous version

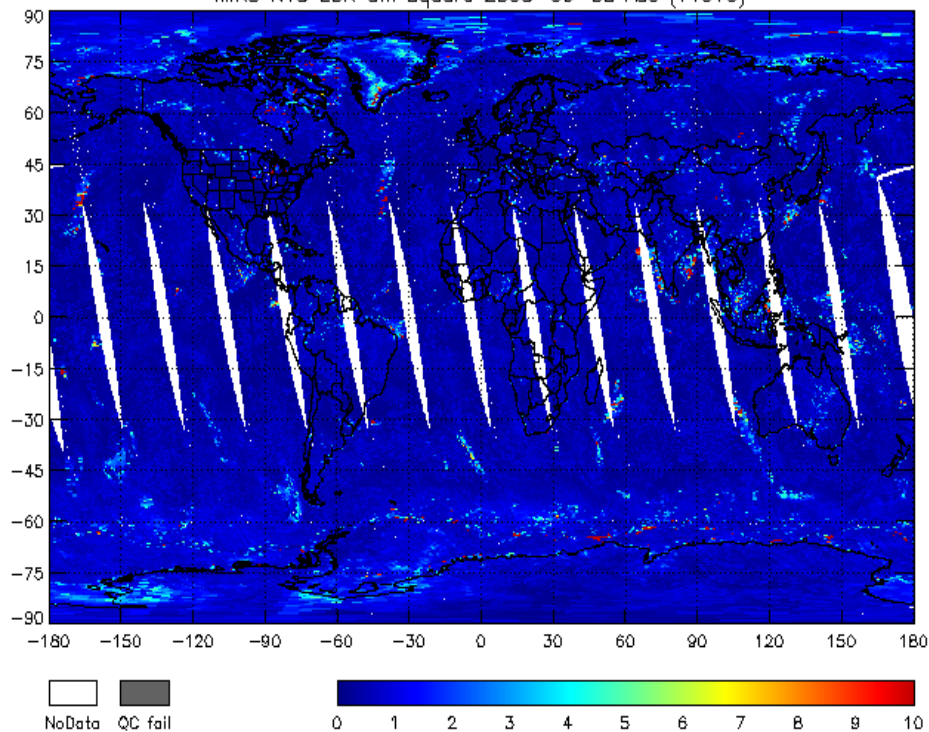
(non convergence when precip/ice present)

MIRS N18 EDR Chi Square 2008-04-02 Asc (V1071)



Current version

MIRS N18 EDR Chi Square 2008-06-08 Asc (V1316)





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Hydrometeors Inversion Approach

**MIRS Core Products
(from 1DVAR)**
CLW, IWP and RWP

Sensor-independent Function which allows expanding to all sensors easily (pending 1DVAR core products)

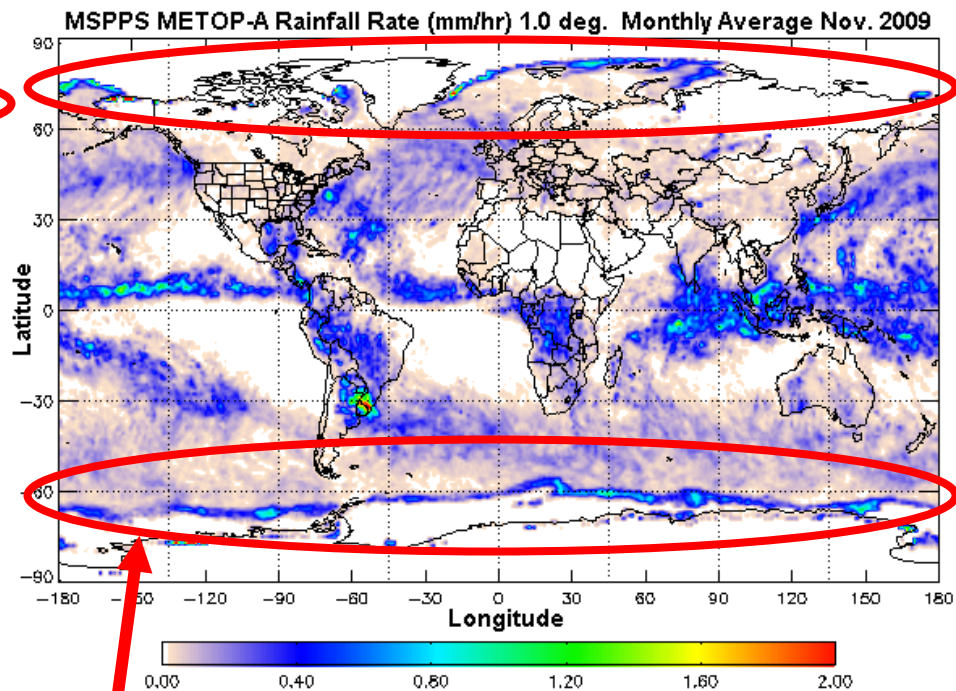
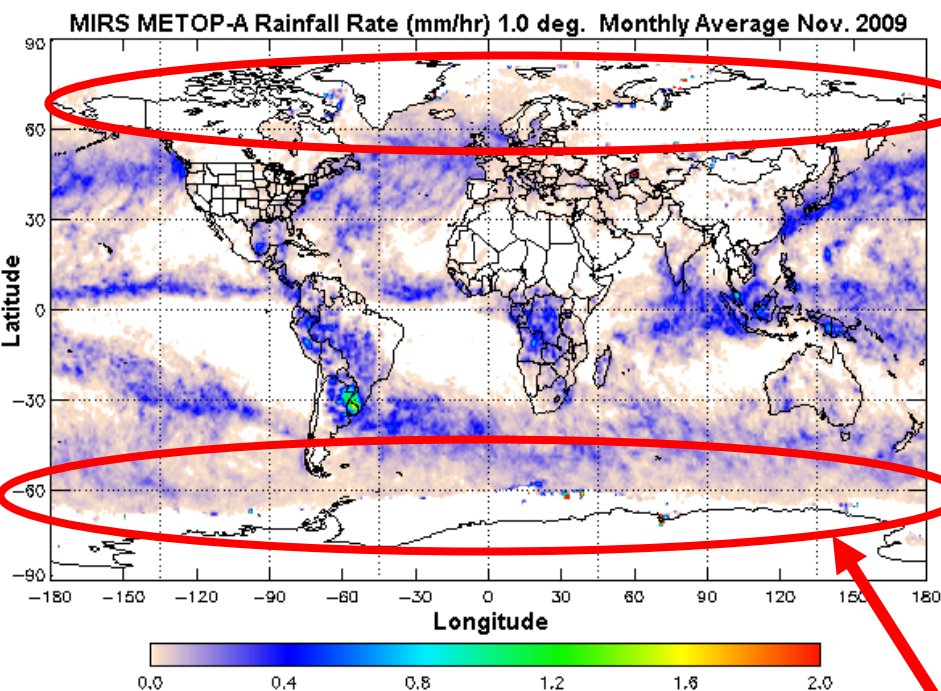
Hydrometeors are hard to validate. RR is easier to assess (wrt ground-based radar, gauges). Assessing RR is an indirect validation of IWP, CLW, RWP.

Inversion Algorithm
 $RR = a_1 IWP + a_2 CLW + a_3 RWP$

**MIRS Rainfall Rate
(mm/hr)**

MiRS Monthly composite (Metop-A) 1DVAR

MSPPS Monthly composite (Metop-A) *Heritage algorithm: based on physical regression*

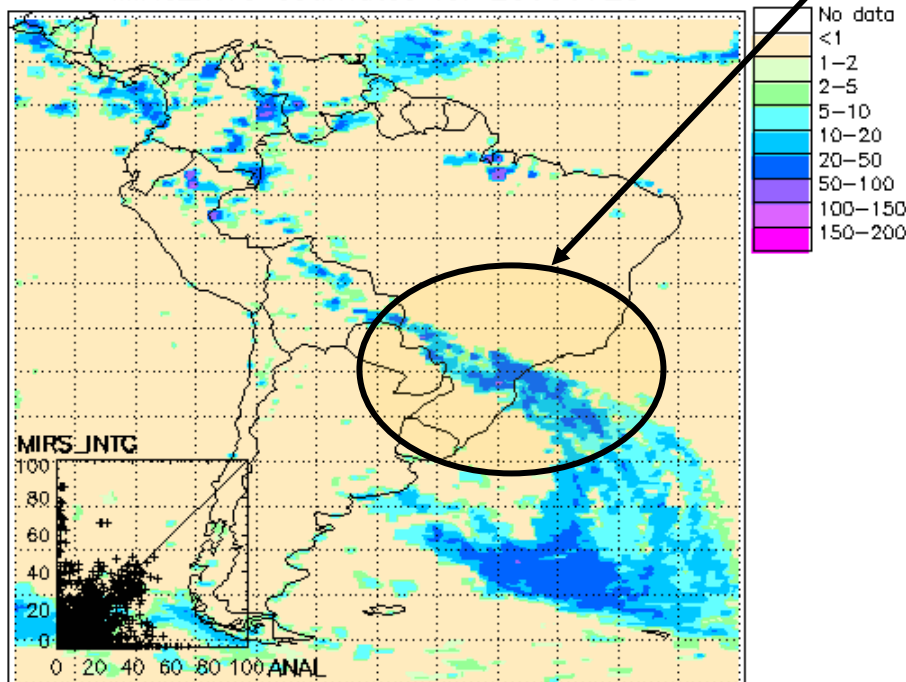


Significant reduction in Rain false alarm using MiRS, at surface transitions and edges

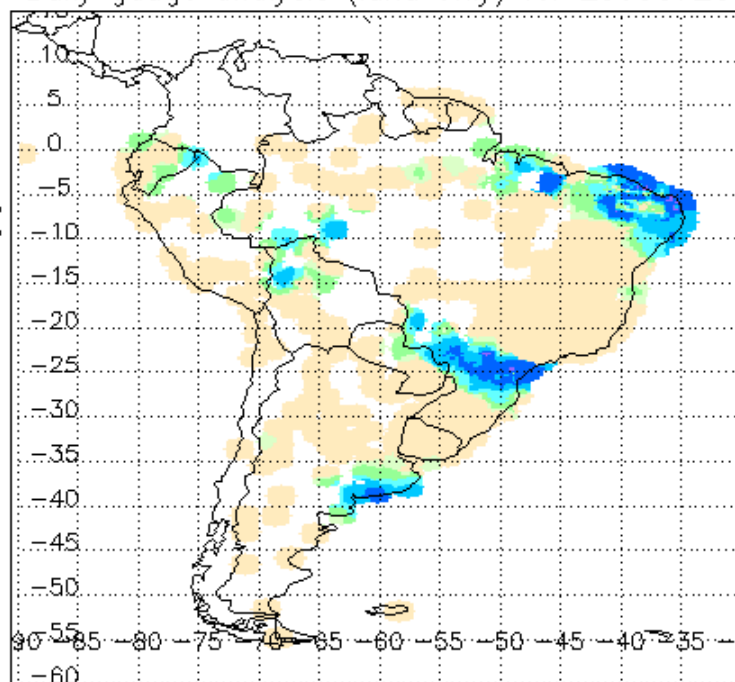
MiRS RR part of IPWG Intercomparison (N. America, S. America and Australia sites)

No discontinuity at coasts (MiRS applies to both land and ocean)

MiRS_INTG estimates for 20090723



Daily gauge analysis (land only) for 20090723



Daily fraction by occurrence



Daily fraction of total rain



Rainfall accumulation by amount

MiRS_INTG

<1 ≥1

	<1	≥1
<1	10390	689
≥1	3228	1400

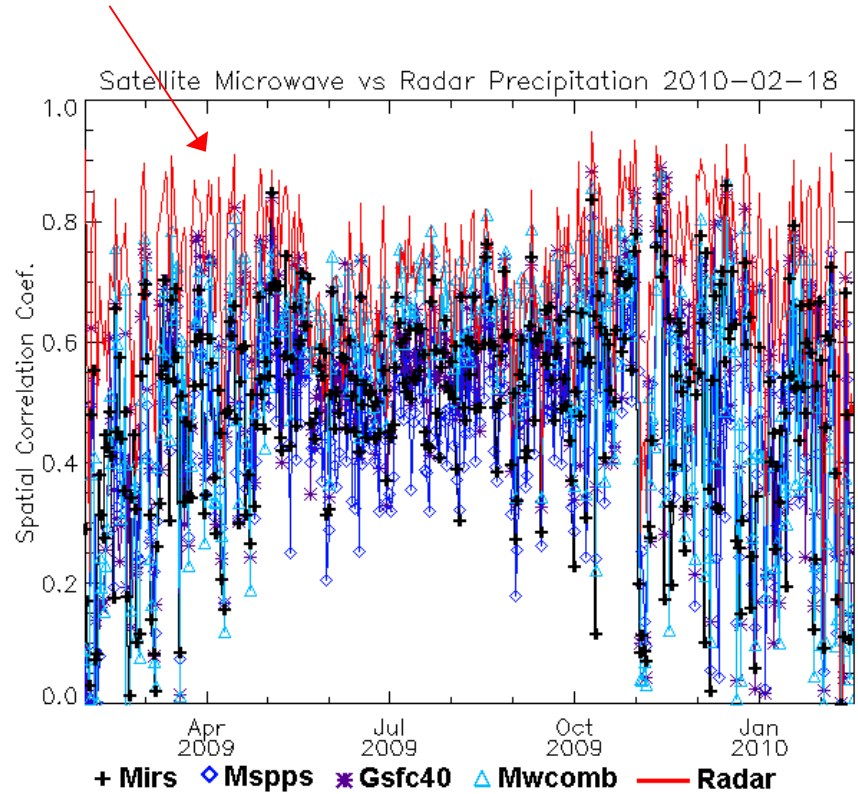
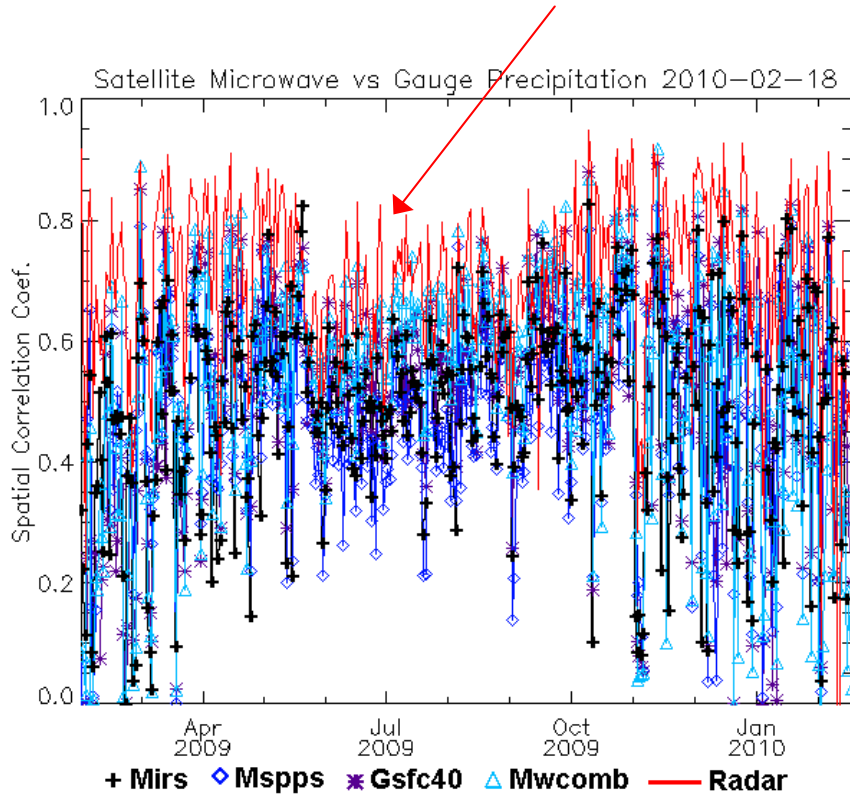
Verification statistics for 20090723 n=15707 Verif. grid=0.25° Units=mm/d

Analysed MiRS_INTG

	<1	≥1
# gridpoints raining	4628	2089
Average rain	3.0	1.7
Conditional rain	10.0	12.4
Rain volume (mm*km ² *10 ⁶)	33.1	18.5
Maximum rain	69.5	85.4

Mean abs error = 3.0
 RMS error = 7.8
 Correlation coeff = 0.341
 Frequency bias = 0.451
 Probability of detection = 0.303
 False alarm ratio = 0.330
 Hanssen & Kuipers score = 0.240
 Equitable threat score = 0.167

Upper Limit set by the Rain Gauge to Rain Radar Comparison

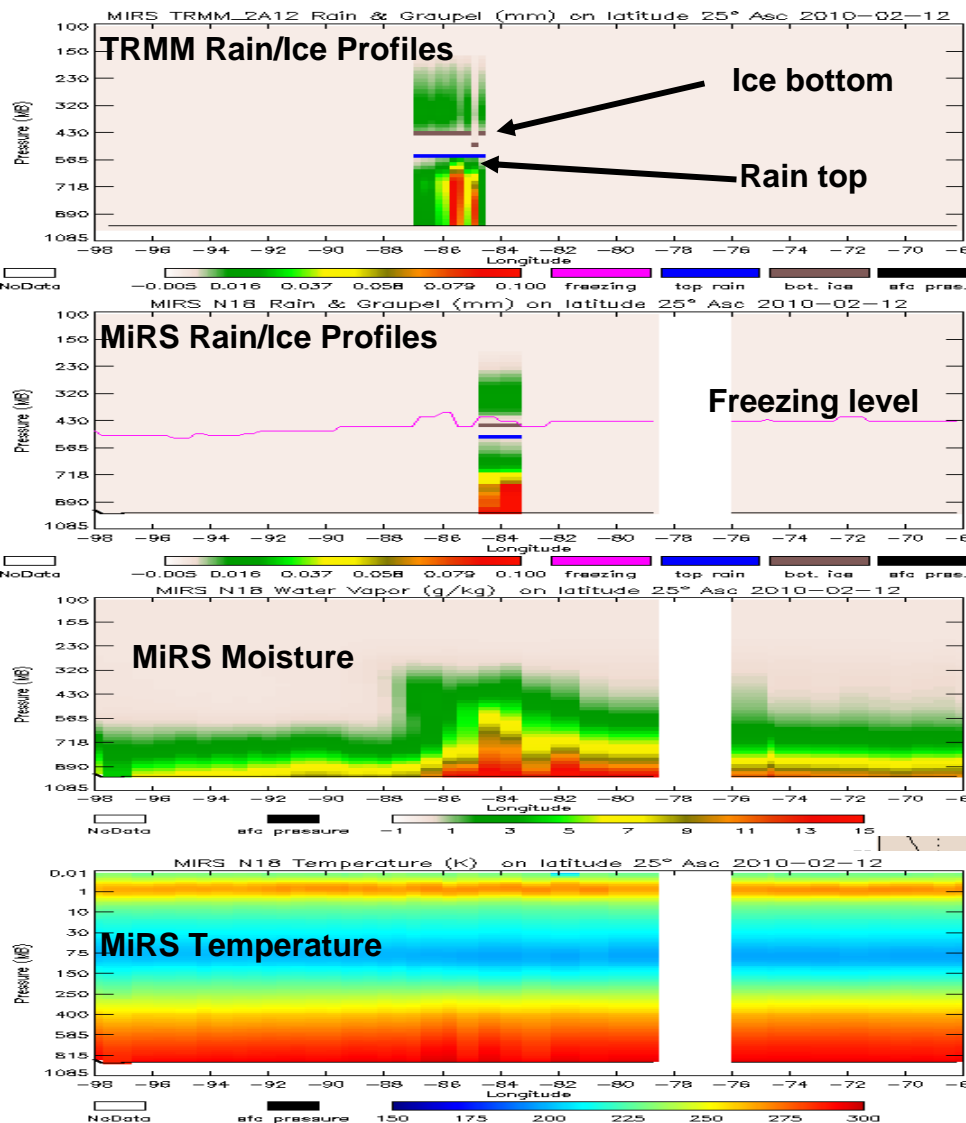




Qualitative check of the Cloudy/Rainy radiance handling



Cross-sections of both TRMM and MiRS products at 25 degrees North



Notes:

- Generally, consistent features between TRMM and MiRS (except for expected shift)
 - Ice is found on top of liquid rain
 - Transition between frozen and liquid is delineated by the freezing level determined from the temperature profile.
 - Moisture increases in and around the rain event
- ↓
- Suggests that these products are reasonably constrained within physical inversion



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- ❖ MiRS is a generic retrieval/assimilation system (N18, N19, Metop-A, DMSP F16/18 SSMIS). Being extended to NPP/ATMS, TRMM/TMI and GPM/Mega-Tropiques
- ❖ All parameters impacting TBs are retrieved simultaneously: sounding, emissivity, skin temperature, cloud, rain, ice, allowing point-to-point variation of emissivity over land
- ❖ Final solution fits measurements (a necessary requirement).
- ❖ Inclusion of hydrometeors in retrieval allows processing cloud/rain –impacted radiances. Non-linear cloud-precip clearing.
- ❖ Physical Constraints are included through Covariance.
- ❖ Assessment of hydrometeors performed using RR as proxy.
- ❖ Results show that MiRS RR is consistent with established algorithms perfs, with the added value of a physically consistent solution.



BACKUP SECTION

Cost Function Minimization

❖ Cost Function to Minimize:

$$J(\mathbf{X}) = \left[\frac{1}{2}(\mathbf{X} - \mathbf{X}_0)^T \times \mathbf{B}^{-1} \times (\mathbf{X} - \mathbf{X}_0) \right] + \left[\text{Jacobians \& Radiance Simulation from Forward Operator: CRTM} \right]$$

❖ To find the optimal solution, solve for: $\frac{\partial J}{\partial \mathbf{X}}(\mathbf{X}) = \mathbf{J}'(\mathbf{X}) = 0$

❖ Assuming Linearity $y(\mathbf{x}) = y(\mathbf{x}_0) + \mathbf{K}[\mathbf{x} - \mathbf{x}_0]$

❖ This leads to iterative solution:

$$\Delta \mathbf{X}_{n+1} = \left\{ \left(\mathbf{B}^{-1} + \mathbf{K}_n^T \mathbf{E}^{-1} \mathbf{K}_n \right)^{-1} \mathbf{K}_n^T \mathbf{E}^{-1} \right\} \left[\left(\mathbf{Y}^m - \mathbf{Y}(\mathbf{X}_n) \right) + \mathbf{K}_n \Delta \mathbf{X}_n \right]$$

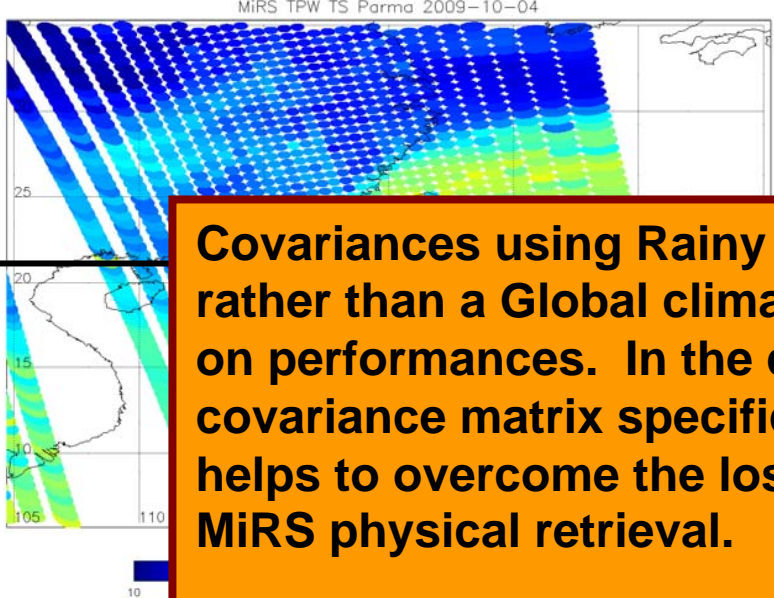
$$\Delta \mathbf{X}_{n+1} = \left\{ \mathbf{B} \mathbf{K}_n^T \left(\mathbf{K}_n \mathbf{B} \mathbf{K}_n^T + \mathbf{E} \right)^{-1} \right\} \left[\left(\mathbf{Y}^m - \mathbf{Y}(\mathbf{X}_n) \right) + \mathbf{K}_n \Delta \mathbf{X}_n \right]$$

More efficient
(1 inversion)

Preferred when $n\text{Chan} \ll n\text{Params}$ (MW)

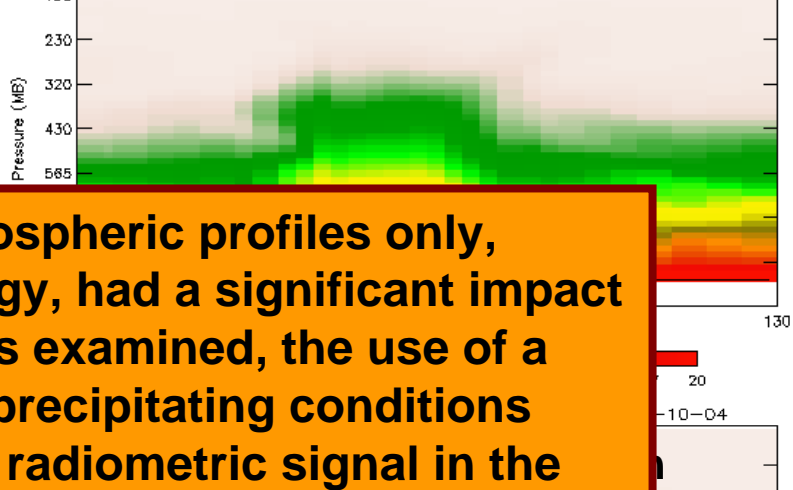
Importance of the Covariance Matrix

TPW Horizontal Field



ECMWF Collo. MIRS N1B Water Vapor (g/kg) on latitude 21° Asc 2009-10-04

ECMWF WV cross-section

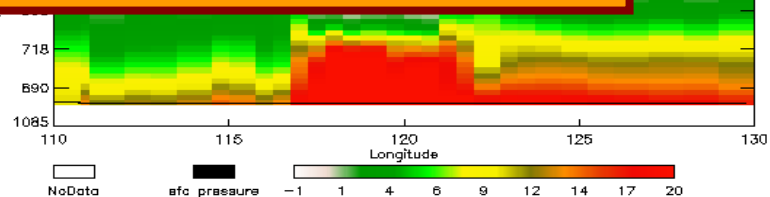
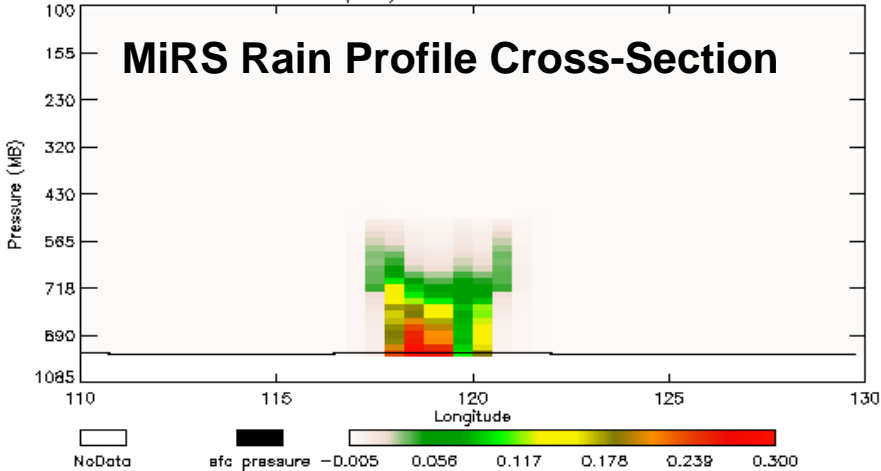


Covariances using Rainy atmospheric profiles only, rather than a Global climatology, had a significant impact on performances. In the cases examined, the use of a covariance matrix specific to precipitating conditions helps to overcome the loss of radiometric signal in the MiRS physical retrieval.

Climatology Background

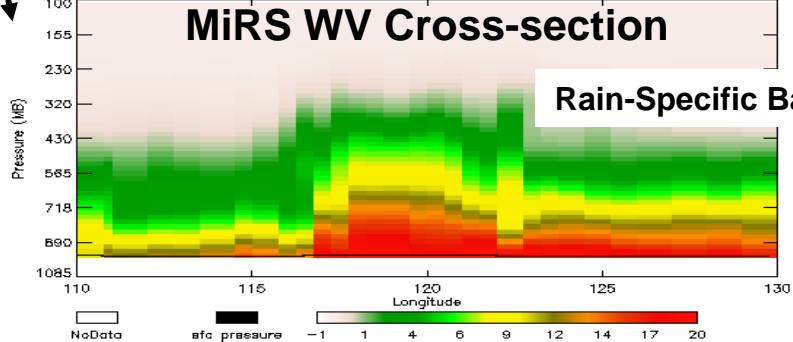
MIRS N1B Rain (mm) on latitude 21° Asc 2009-10-04

MiRS Rain Profile Cross-Section



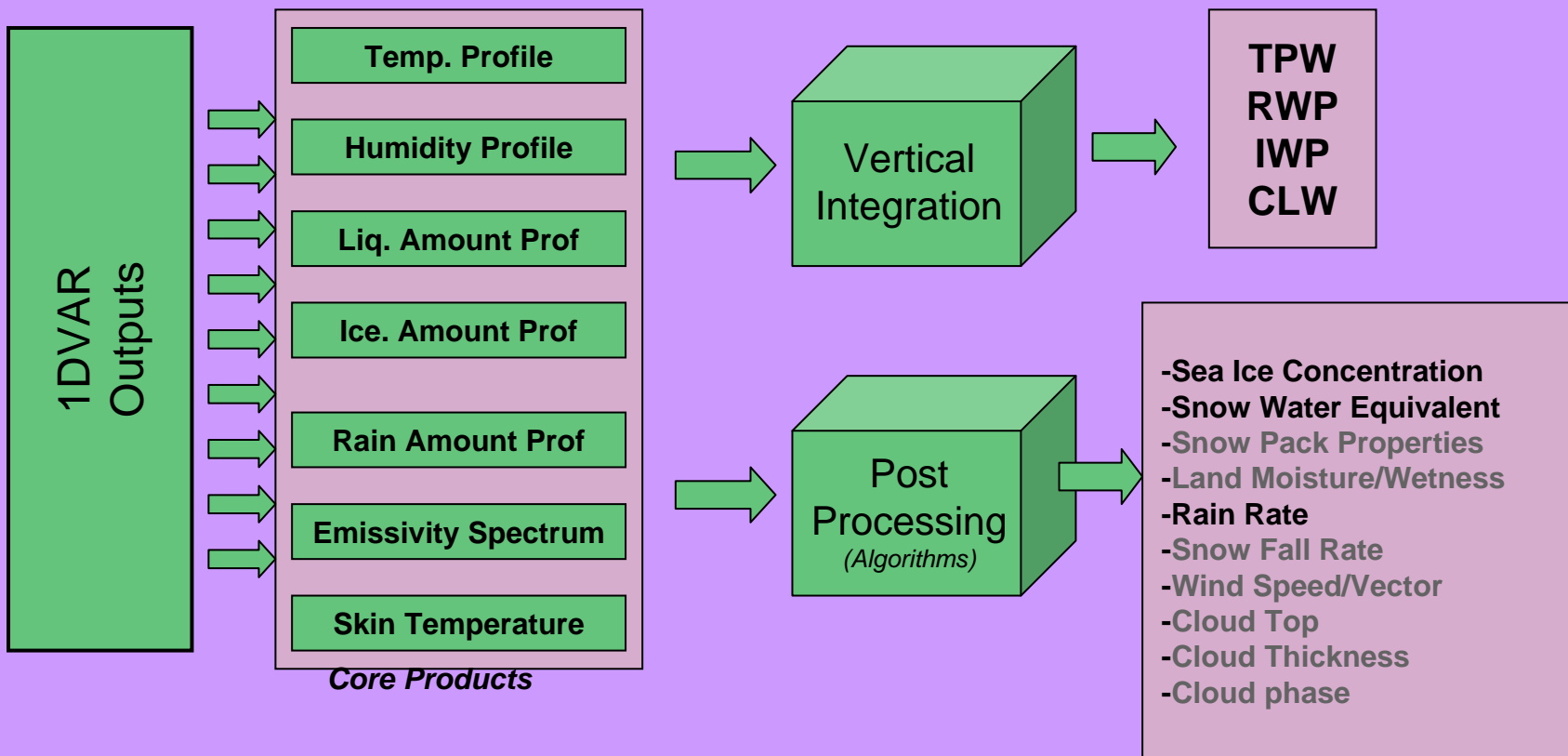
MIRS N1B Water Vapor (g/kg) on latitude 21° Asc 2009-10-04

MiRS WV Cross-section



Rain-Specific Background

Vertical Integration and Post-Processing





All-surfaces: Variational Handling of Surface-Sensitive Channels



- ❖ Similar to handling cloud and hydrometeors, MiRS approach to account for surface-sensitivity of channels is by accounting for emissivity vector within state vector.

- ❖ Advantages:
 - Extend retrieval to all surfaces (only difference is background covariance and mean used). *Example: TPW over land.*
 - Generating an emissivity vector product, clear from atmospheric effects (used for a more accurate estimate of surface parameters)
 - Consistent treatment of all parameters globally (same methodology). *Example: RR is retrieved over ocean and land using the same code.*
 - Greater physical distinction between T_{skin} and Emissivity (based on physical Jacobians and different spectral signatures)
 - Allows a point to point variation of emissivity (useful for coasts, after rain, etc)

- ❖ Disadvantages:
 - Great emphasis must be given to the balance between different parameters (so that emissivity does not become a sink hole for variability due to other parameters such as cloud: hard)
 - Great constraint is put on the accuracy of emissivity



Assumptions Made in Solution Derivation



- ❖ The PDF of X is assumed Gaussian
- ❖ Operator Y able to simulate measurements-like radiances
- ❖ Errors of the model and the instrumental noise combined are assumed (1) non-biased and (2) Normally distributed.
- ❖ Forward model assumed locally linear at each iteration.



Retrieval in Reduced Space (EOF Decomposition)



- ❖ All retrieval is done in EOF space, which allows:
 - Retrieval of profiles (T,Q, RR, etc): using a limited number of EOFs
 - More stable inversion: smaller matrix but also quasi-diagonal
 - Time saving: smaller matrix to invert

❖ Mathematical Basis:

- EOF decomposition (*or Eigenvalue Decomposition*)
 - By projecting back and forth Cov Matrix, Jacobians and X

$$\Theta = L^T \times B \times L$$

Diagonal Matrix
(used in reduced space retrieval)

Transf. Matrix
(computed offline)

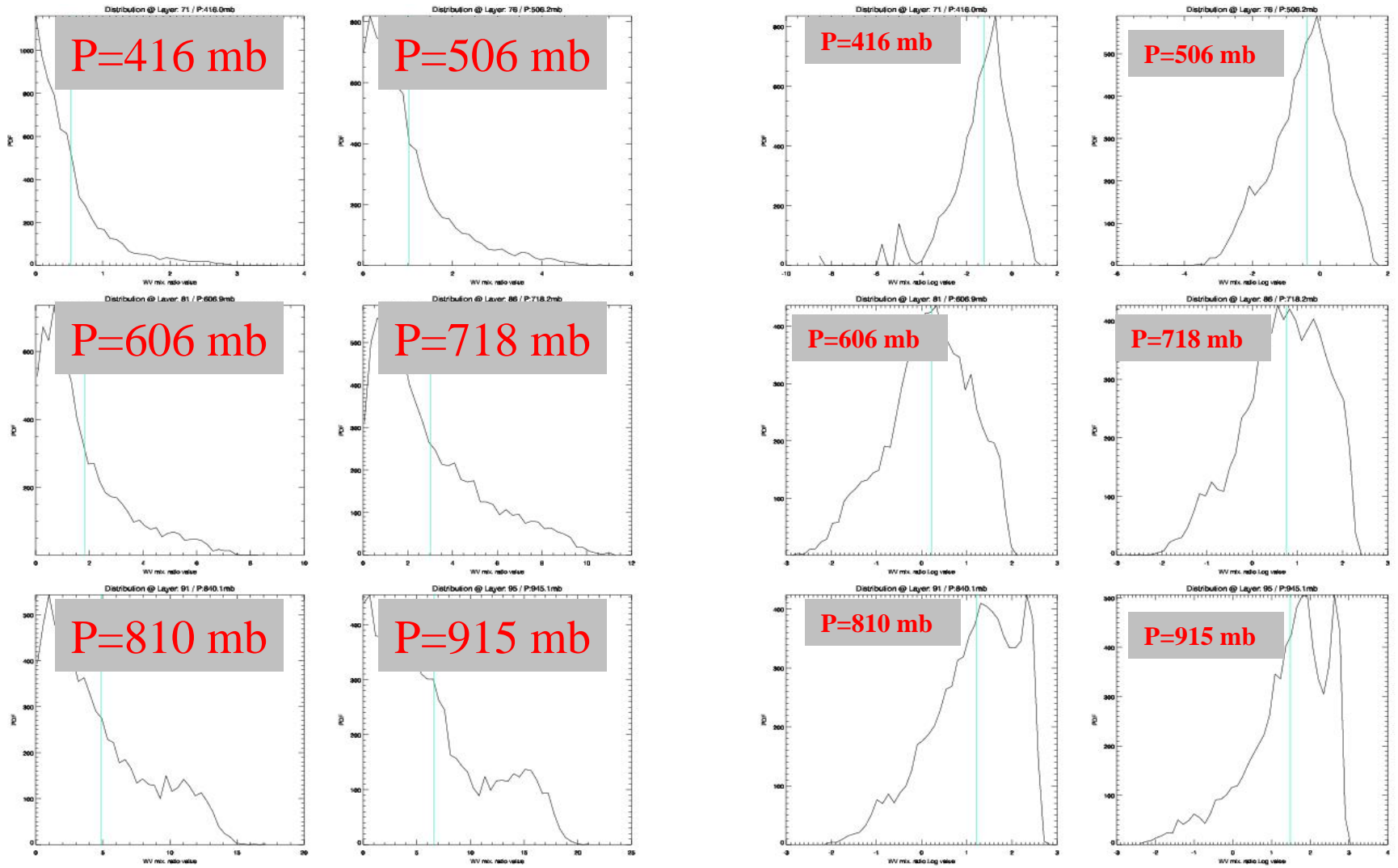
Covariance matrix
(geophysical space)



Retrieval in Logarithm Space



Advantages: (1) Distributions made more Gaussian & (2) No risk of having unphysical negative values

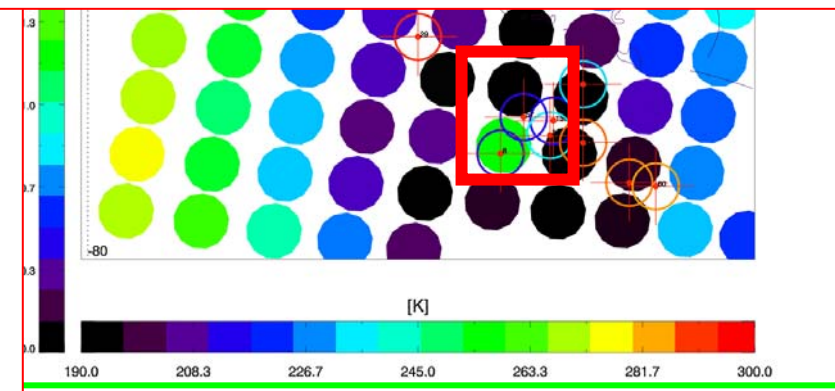
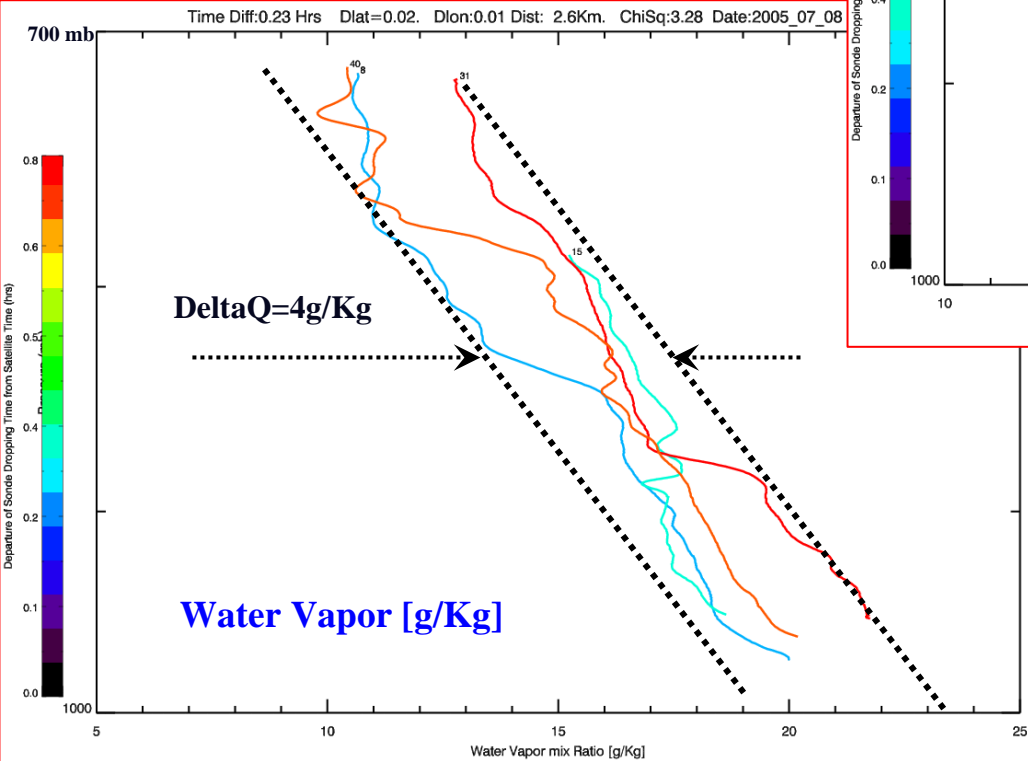
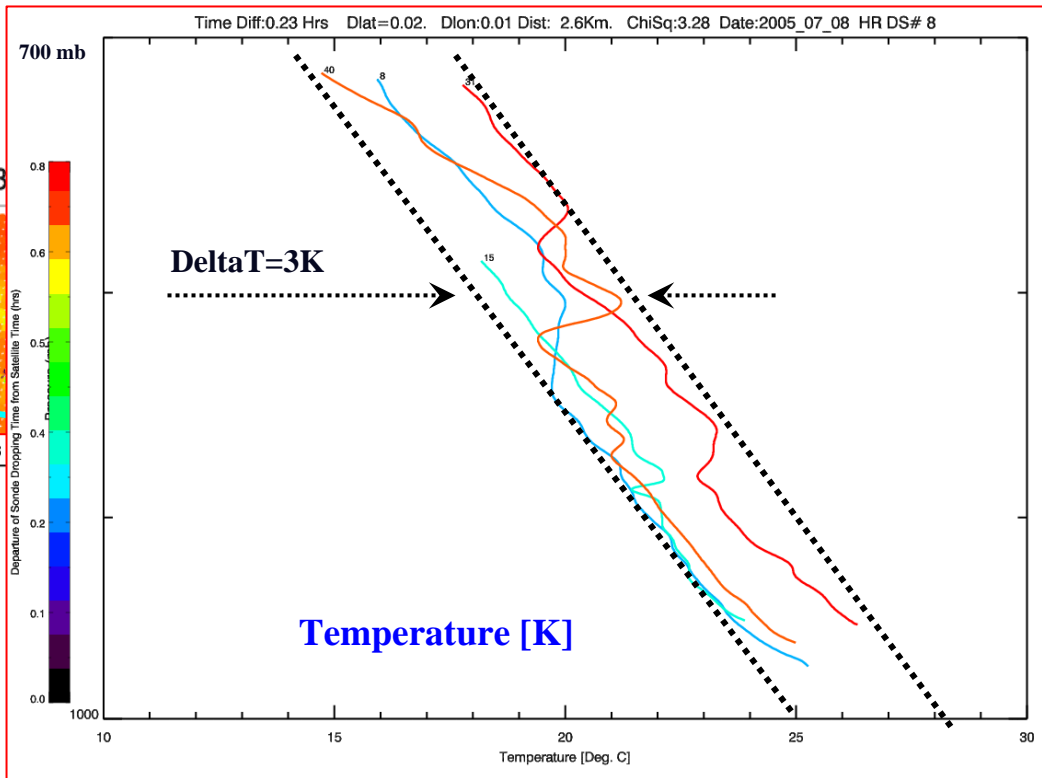
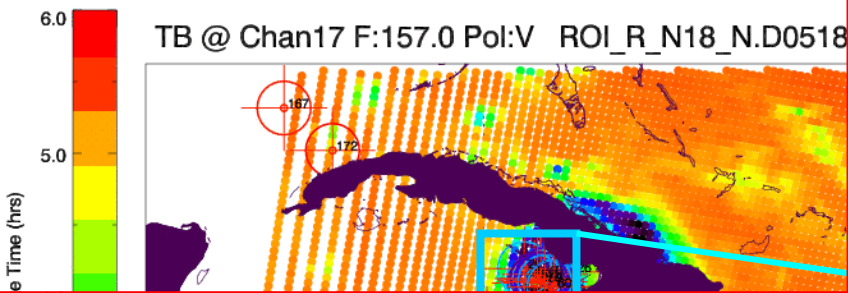


Applied to WV, Cloud and precip

$$J_I = \frac{\partial R}{\partial \text{Log}(x)} = \frac{\partial R}{\partial x} \times \frac{\partial x}{\partial \text{Log}(x)} = J \times x$$

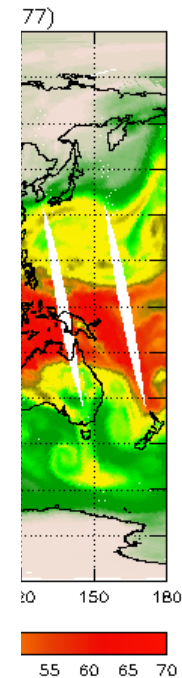
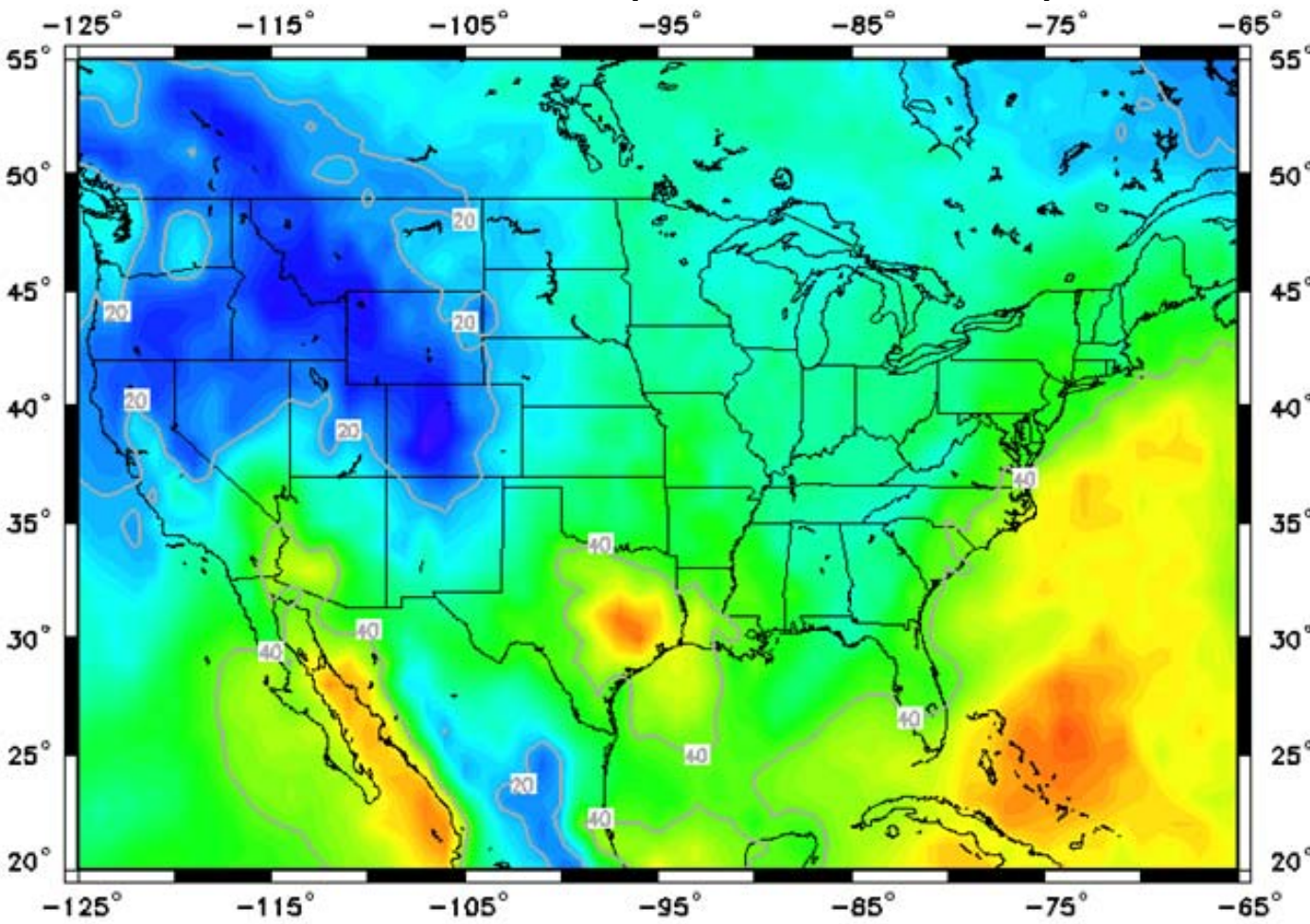
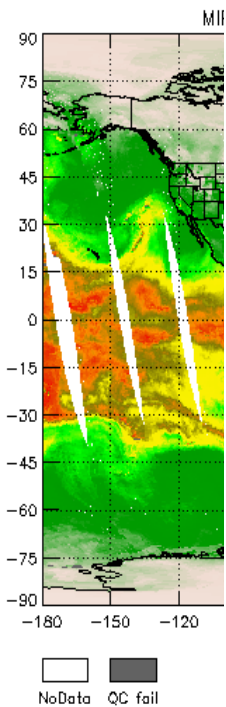


Challenges of Profiling in Active Areas



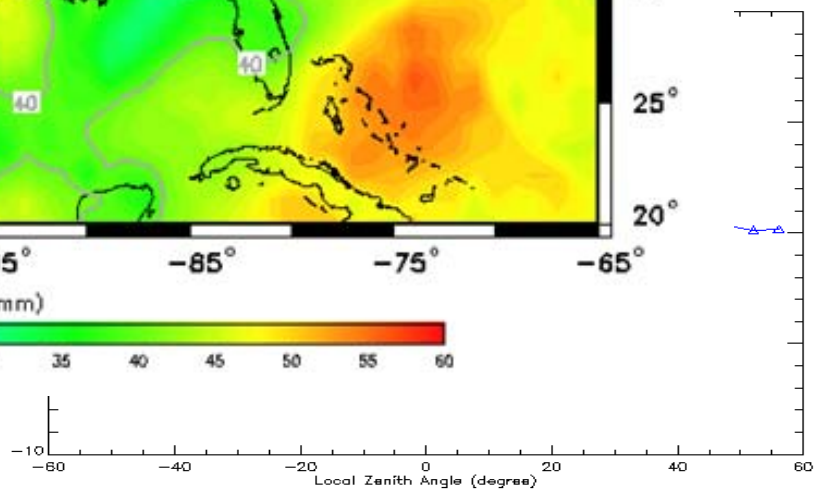
TPW Global Coverage

MiRS TPW Retrieval (zoom over CONUS)



Very si

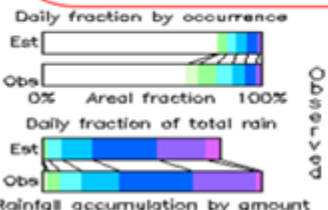
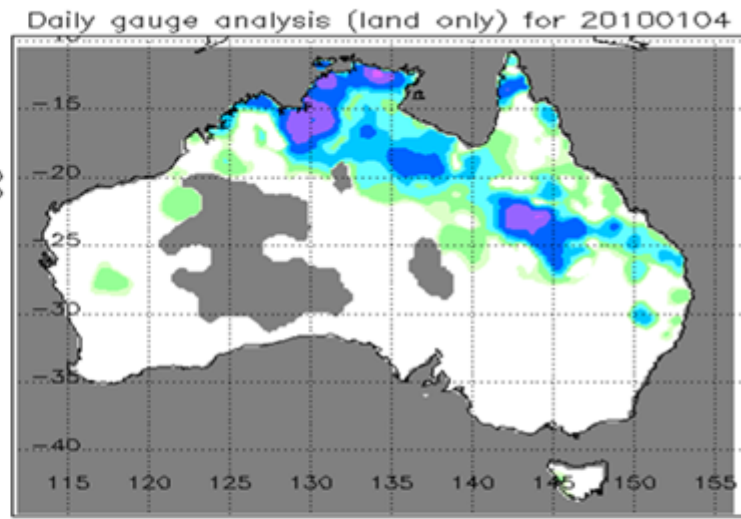
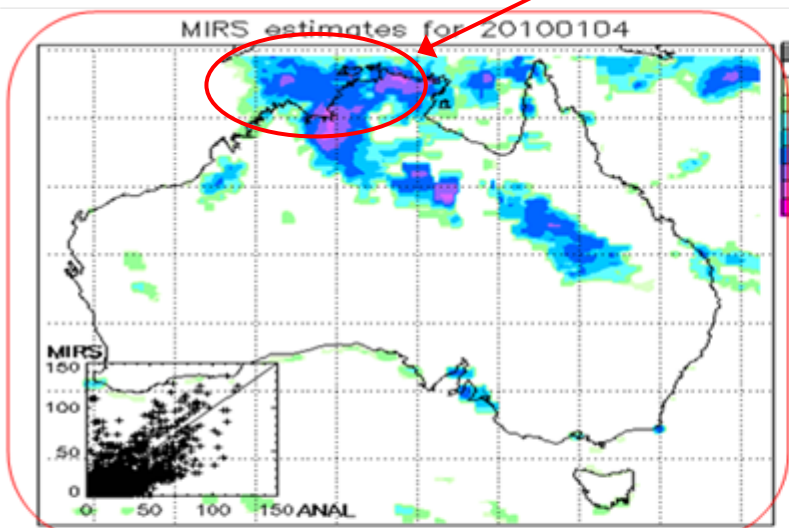
Smooth



No Discontinuities at Coast

Validation over Australia

Rain Gauge



	MIRS	
	<1	≥1
<1	6116	363
≥1	1675	1681

Verification statistics for 20100104 n=9835 Verif. grid=0.25° Units=mm/d

	Analysed	MIRS
# gridpoints raining	3356	2044
Average rain	5.0	4.1
Conditional rain	14.7	19.7
Rain volume (mm*km ² *x10 ⁶)	33.7	27.5
Maximum rain	118.7	135.8

Mean abs error = 3.6
 RMS error = 9.0
 Correlation coeff = 0.756
 Frequency bias = 0.609
 Probability of detection = 0.501
 False alarm ratio = 0.178
 Hanssen & Kuipers score = 0.445
 Equitable threat score = 0.326

Courtesy of Elizabeth E. Ebert, Bureau of Meteorology, Australia