Recent Developments on the Assimilation of Cloudy Radiances with WRF

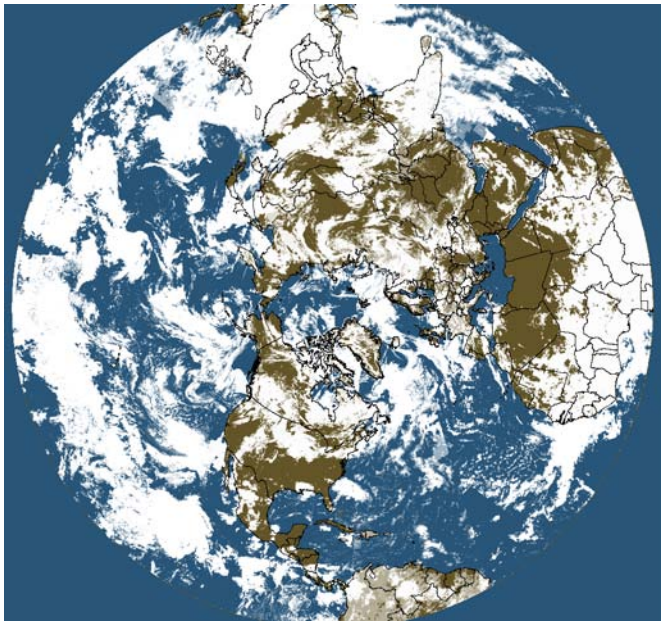
Tom Auligné

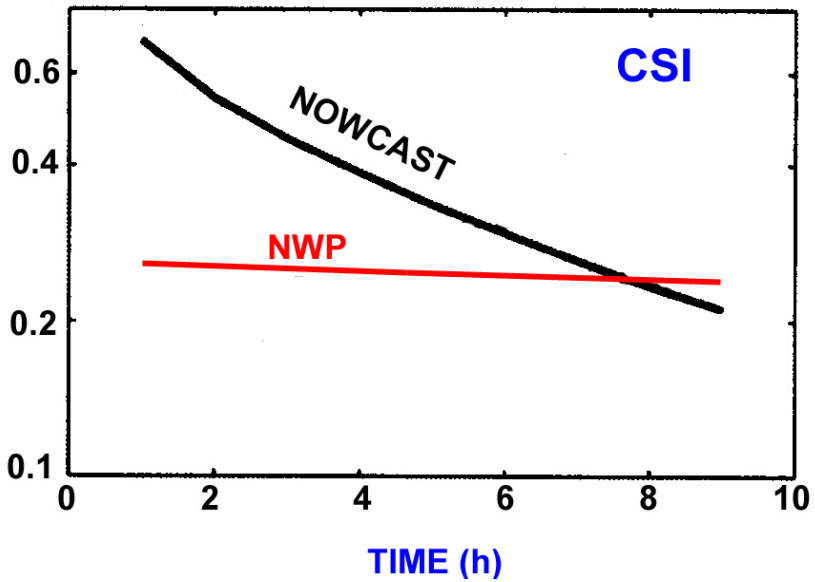
Aimé Fournier, Hans Huang, Hui-Chuan Lin, Zhiquan Liu, Yann Michel, Thomas Nehrkorn, Syed Rizvi, Xin Zhang

JCSDA Seminar- Washington, DC - Nov 10, 2010

The AFWA Coupled Analysis and Prediction System (ACAPS) project

World-
Wide
Merged
Cloud
Analysis





0.1 mm hourly precipitation skill scores over 21 days
From Lin et al. (2005), courtesy Jenny Sun

GOAL: Develop an analysis and prediction system of 3D cloud properties combined with the dynamical variables.

Outline

- Cloud-affected Satellite Radiances
  - Retrieval of Cloud properties
  - Representativeness Error
- Analysis Control Variable
  - Inhomogeneous, flow dependent background errors
  - Displacement Analysis

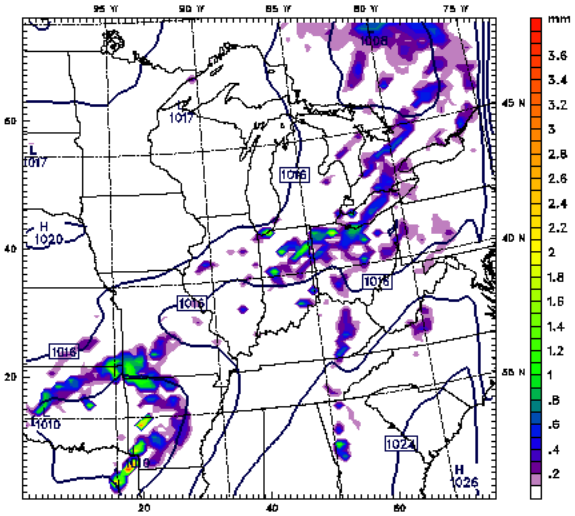
Cloud-affected Satellite Radiances

Assimilation of simulated MW cloud-affected radiances in WRF 3DVar

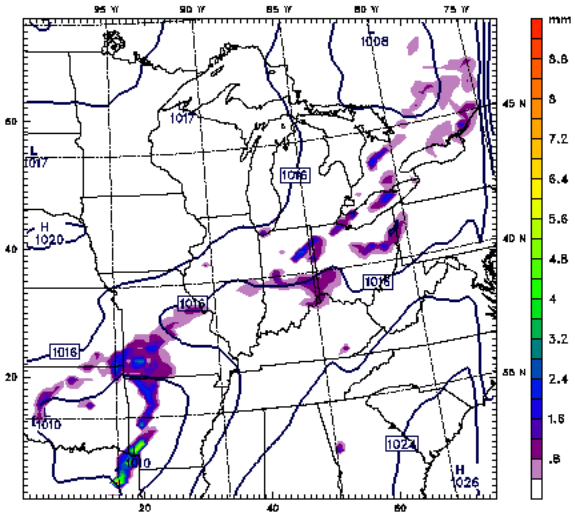
- Use total water $Q_t=Q_{wv}+Q_{clw}+Q_{rain}$ instead of individual hydrometeors as a control variable
- *Use a warm-rain microphysics scheme's TL&AD for partitioning Q_t increment into Q_{wv}, Q_{clw} & Q_{rain}. (Xiao et al., 2007)*
- CRTM as cloudy radiance observation operator
- *Minimization starts from a cloud-free background, this scenario can be realistic for less accurate cloud/precip. forecast in the real world*
- Perfect background for other variables (T,Q etc.)
- *Perfect observations (no noise added to the simulated Tbs)*
- 2 outer-loops

Simulated SSMI/S radiances: 3DVar

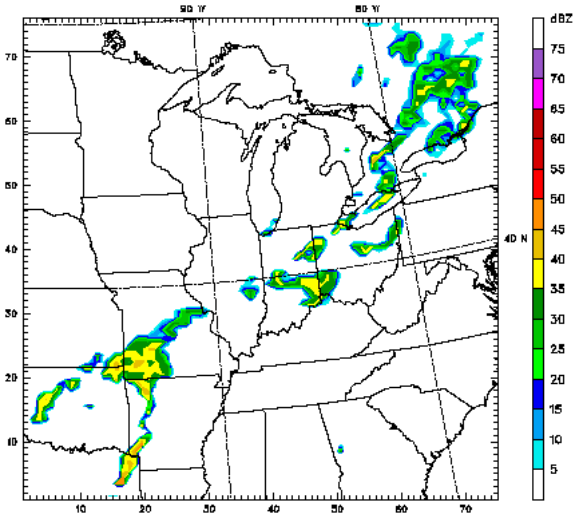
Column-Integrated cloud water



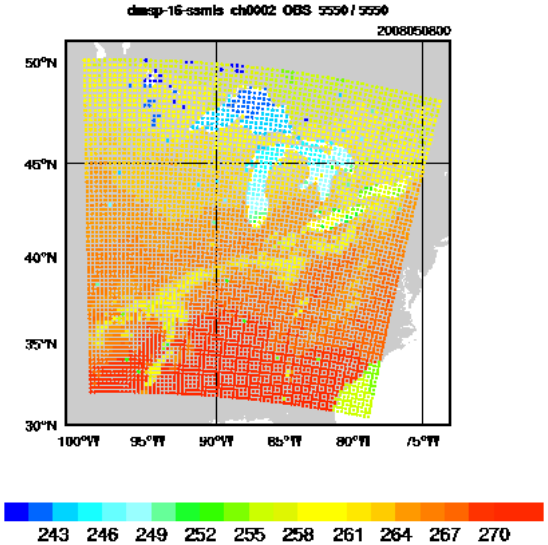
Column-Integrated rain water



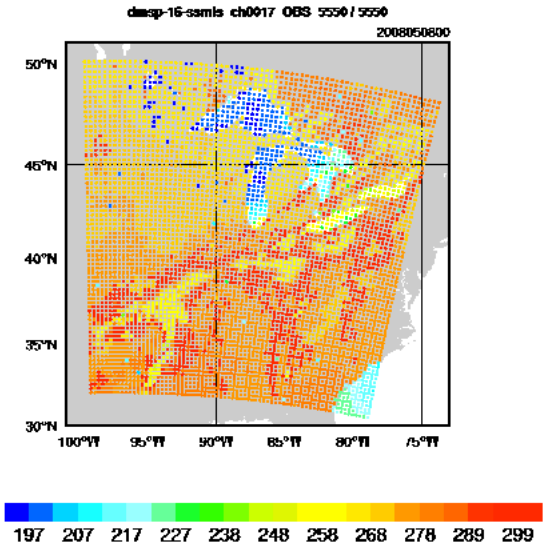
Radar Reflectivity



Simulated Ch2 Tbs



Simulated Ch17 Tbs



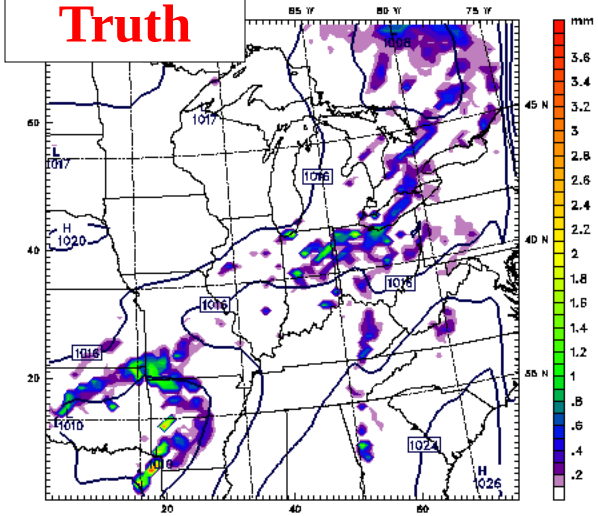
Model = "truth" for SSMI/S radiance simulation

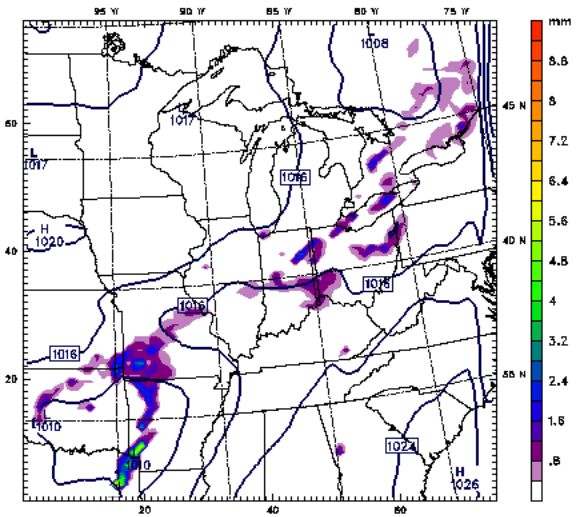
Only liquid hydrometeors considered

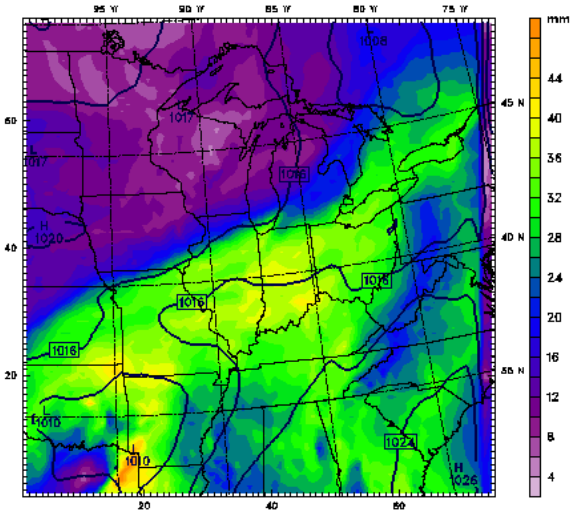
SSMIS radiances (ch 1~6, 8~18) simulated at each grid-point using CRTM

Simulated SSMI/S radiances: 3DVar

Truth

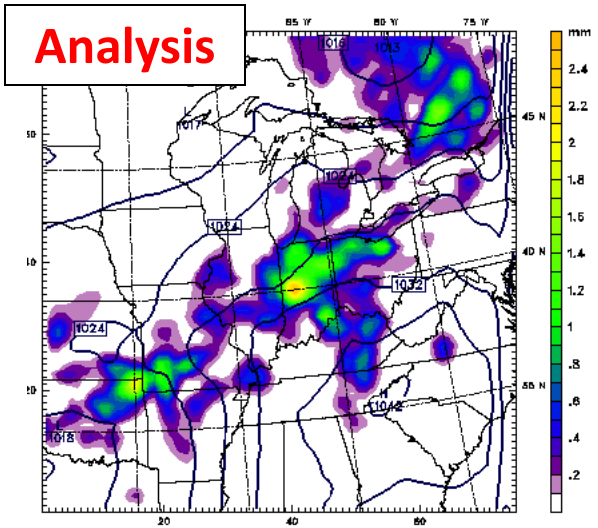


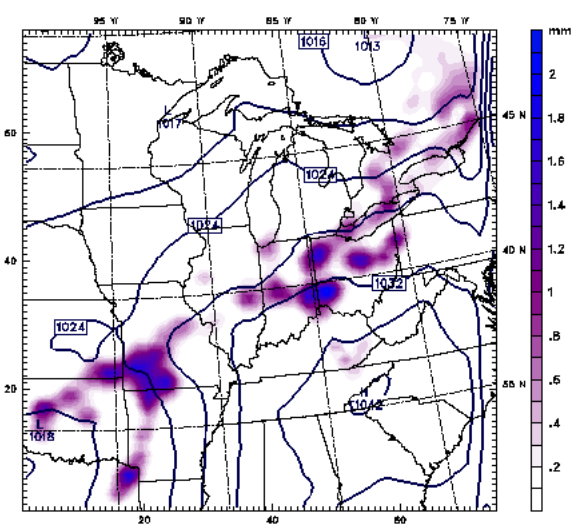


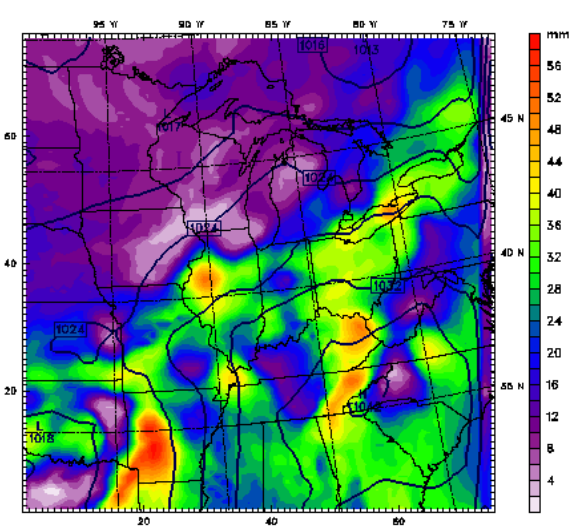


Column-Integrated cloud water | **Column-Integrated rain water** | **Column-Integrated water vapor**

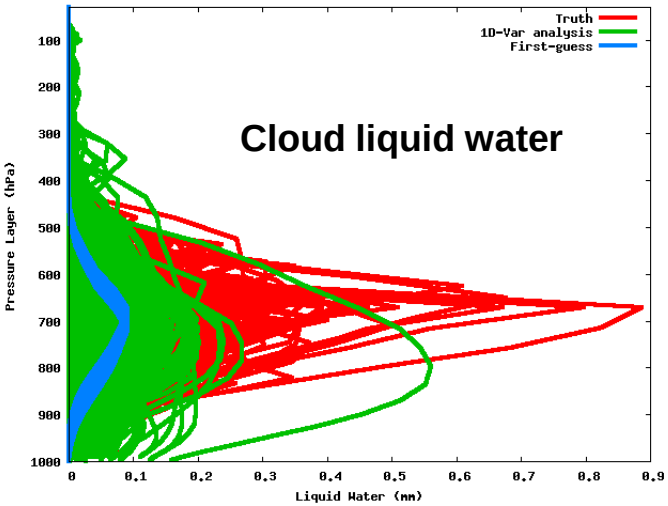
Analysis

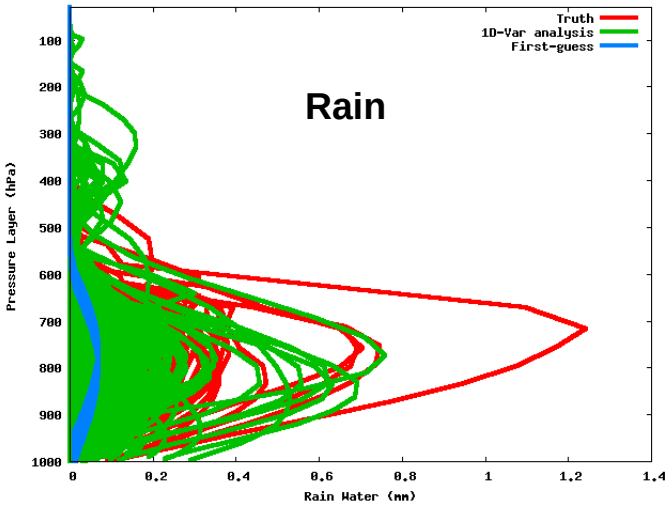


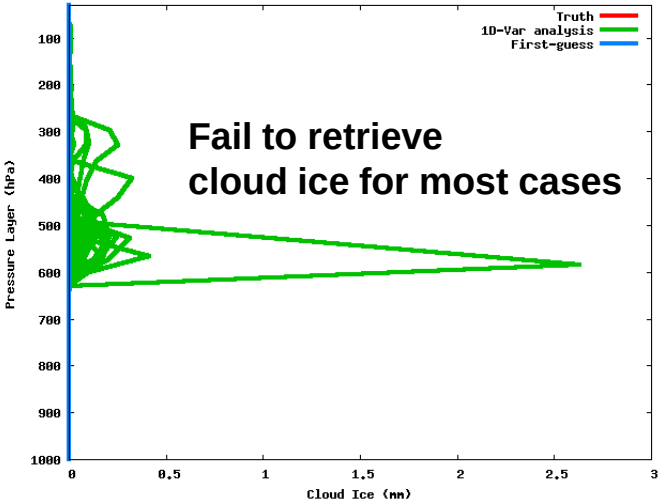




Simulated SSMI/S radiances: 1DVar





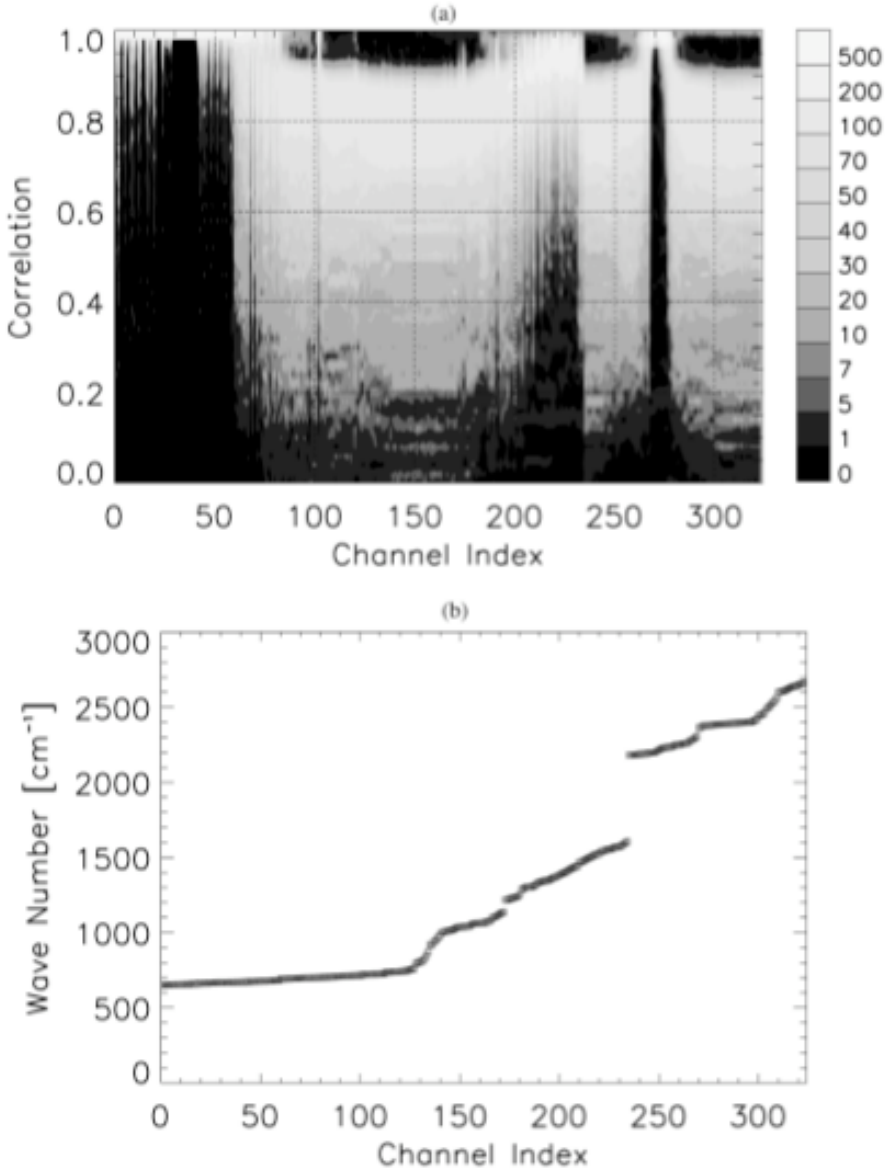


1DVar Retrieval of Hydrometeors

1. Control variables: T, Q, Cloud liquid water, rain, cloud ice
2. Start from a mean cloud/rain profile background
3. Random noise to the simulated obs and T, Q background profiles

Signal for cloud-ice is weaker than for cloud-water/rain

Satellite Infrared Cloudy Radiances



Bi-dimensional histogram of the correlation between linear and non-linear brightness temperature perturbations for AIRS

(Chevallier *et al* 2004)

Cloud Detection for IR sounders

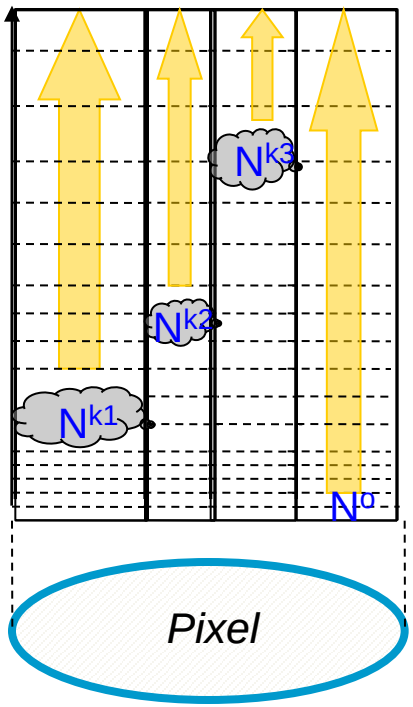
RTM

R_ν^{o} = Radiance calculated in clear sky

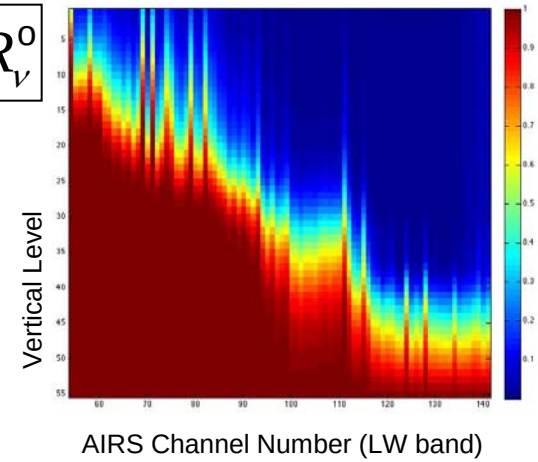
$R_\nu^{\bullet k}$ = Radiance calculated for overcast black cloud at level k

Multivariate Minimum Residual (MMR):

$$R_\nu^{Cld} = N^{o} R_\nu^{o} + \sum_{k=1}^{n} N^{k} R_\nu^{\bullet k}$$



$R_\nu^{\bullet k} / R_\nu^{o}$

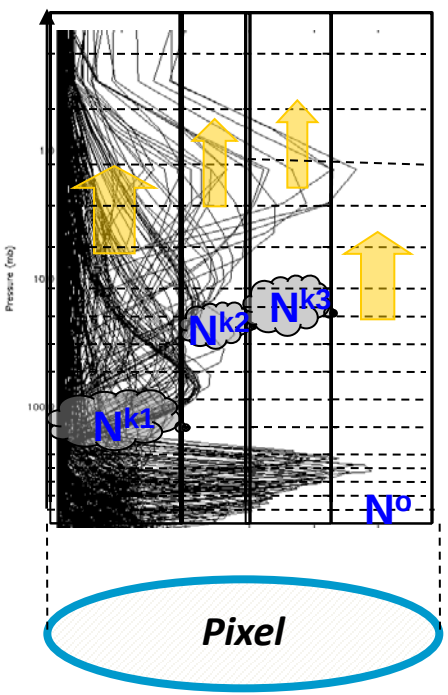


Cloud Detection for IR sounders

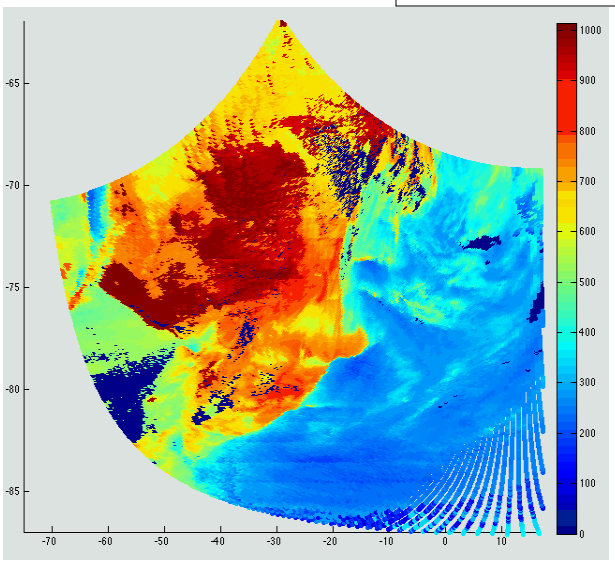
$$R_\nu^{Cld} = N^\circ R_\nu^\circ + \sum_{k=1}^{n} N^k R_\nu^{\bullet k}$$

Cloud fractions N^k are ajusted variationally to fit observations:

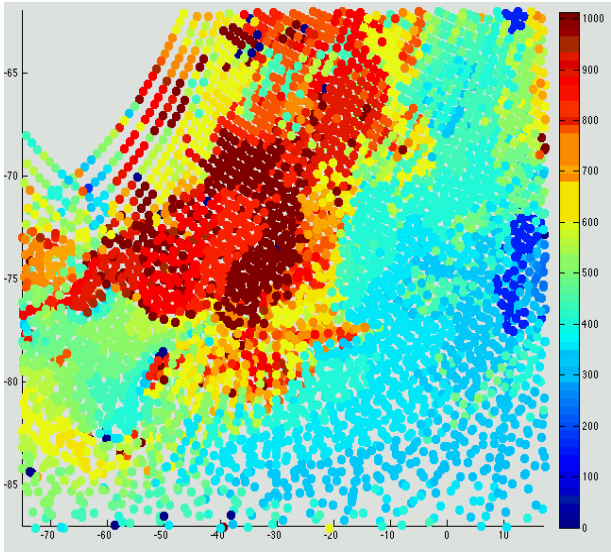
$$J(N) = \frac{1}{2}\sum_\nu \left(\frac{R_\nu^{Cld} - R_\nu^{Obs}}{R_\nu^\circ} \right)^2 \quad \text{with} \quad \begin{cases} 0 \le N^k \le 1, \forall k \in [0,n] \\ N^o + \sum_{k=1}^{n} N^k = 1 \end{cases}$$



Cloud Top Pressure (hPa)



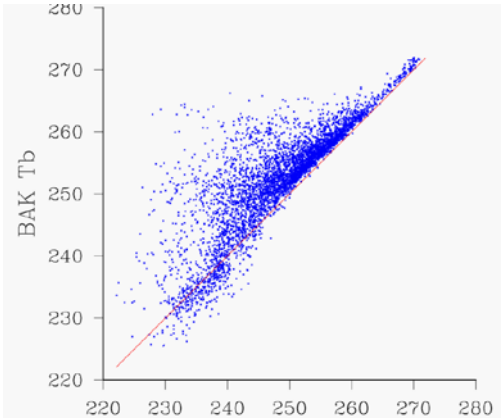
MODIS Level2

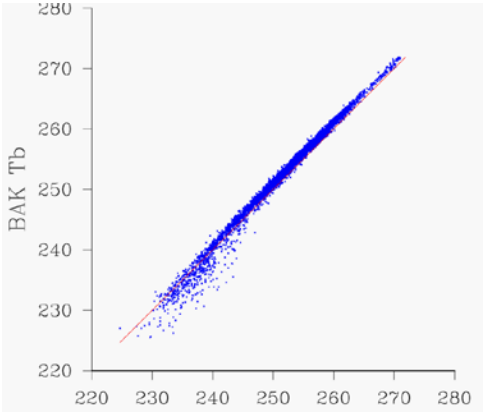


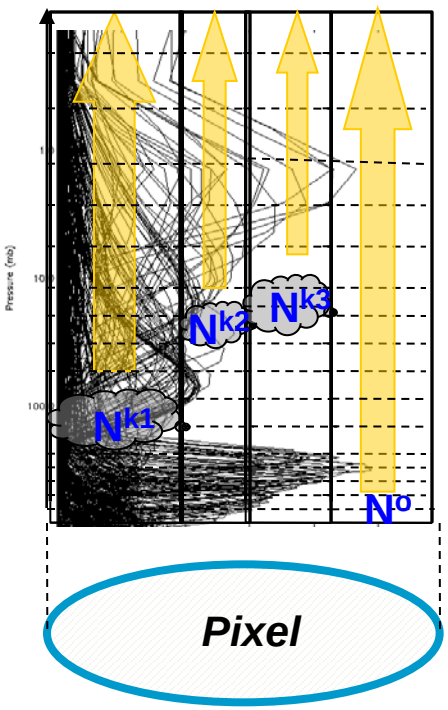
AIRS MMR

IR Cloudy Radiances

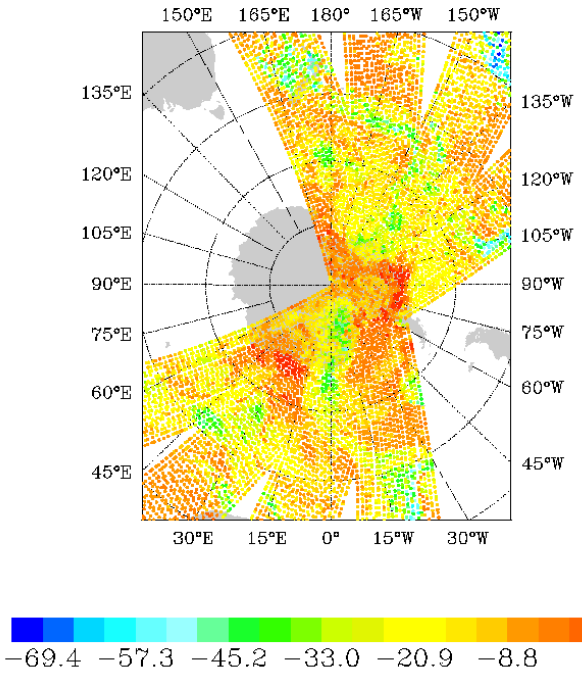
Linear Observation Operator



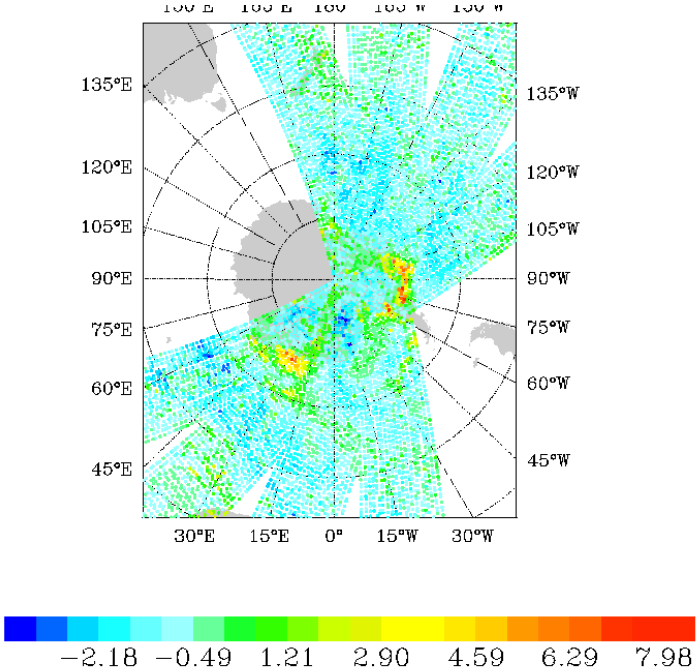




$$R_\nu^{Obs} - R_\nu^{o}$$

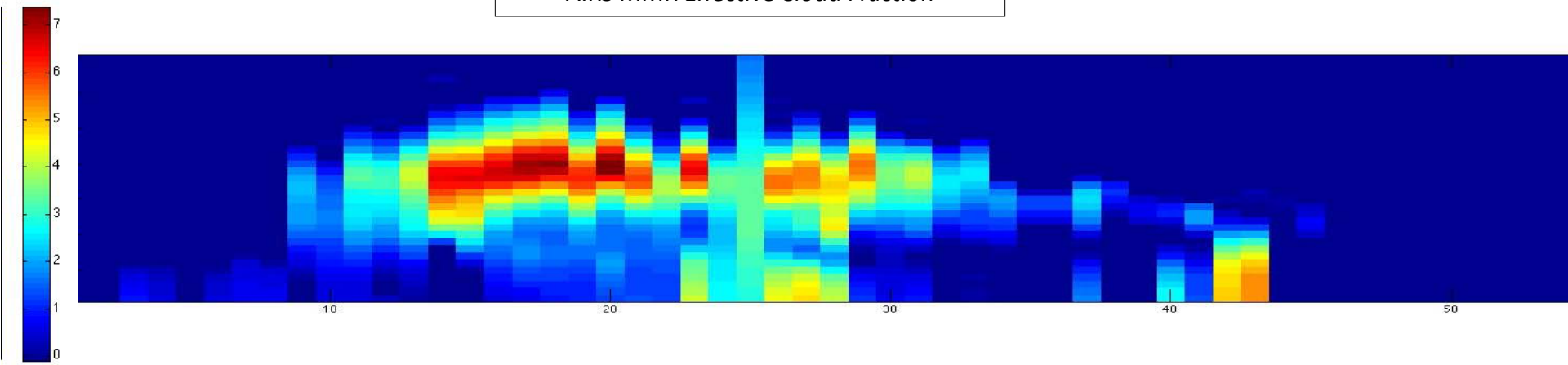


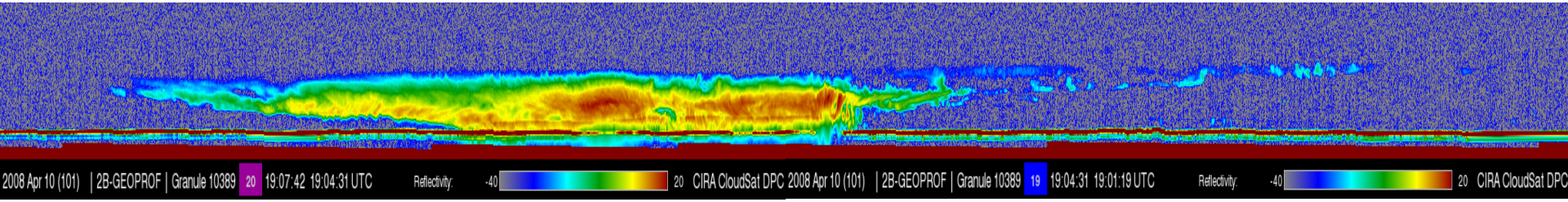
$$R_\nu^{Obs} - R_\nu^{Cld}$$



Cloud Retrieval for IR sounders

AIRS MMR Effective Cloud Fraction

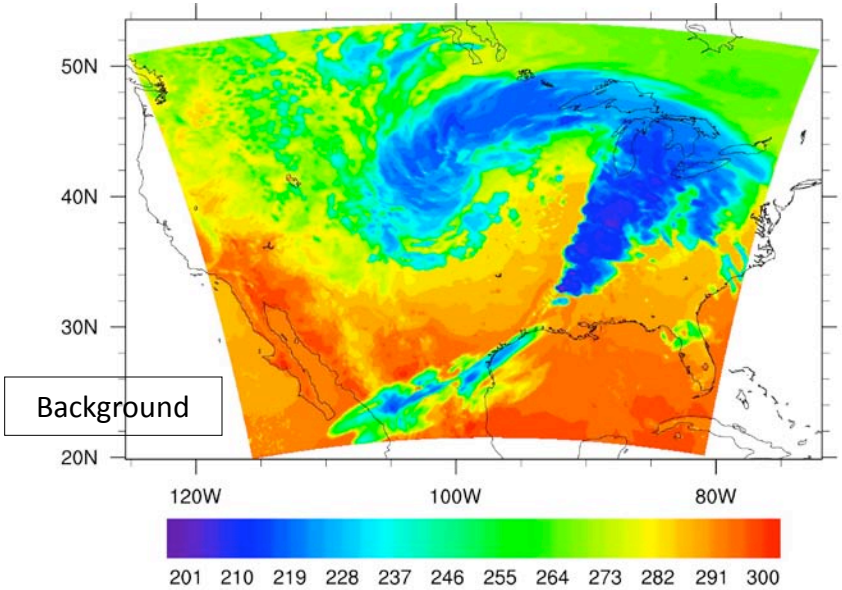




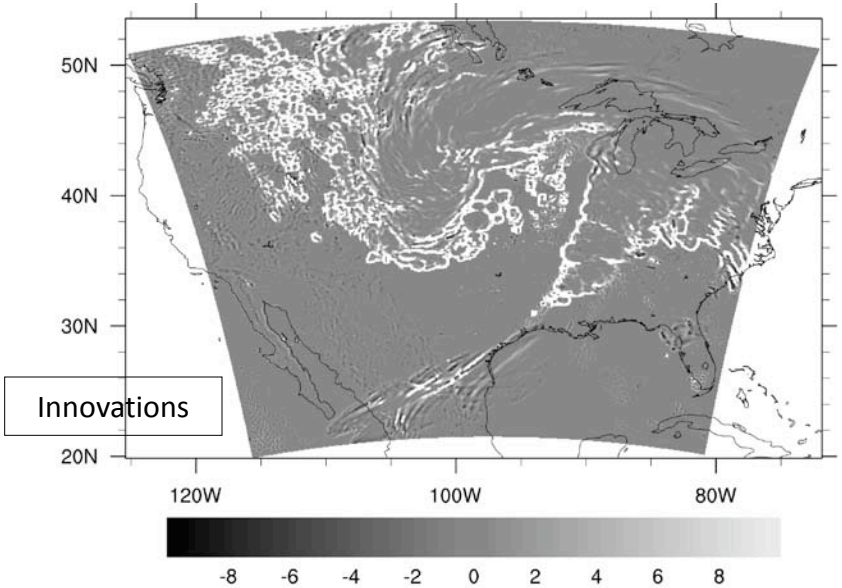
CloudSat Reflectivity

Representativeness Error

Representativeness Error



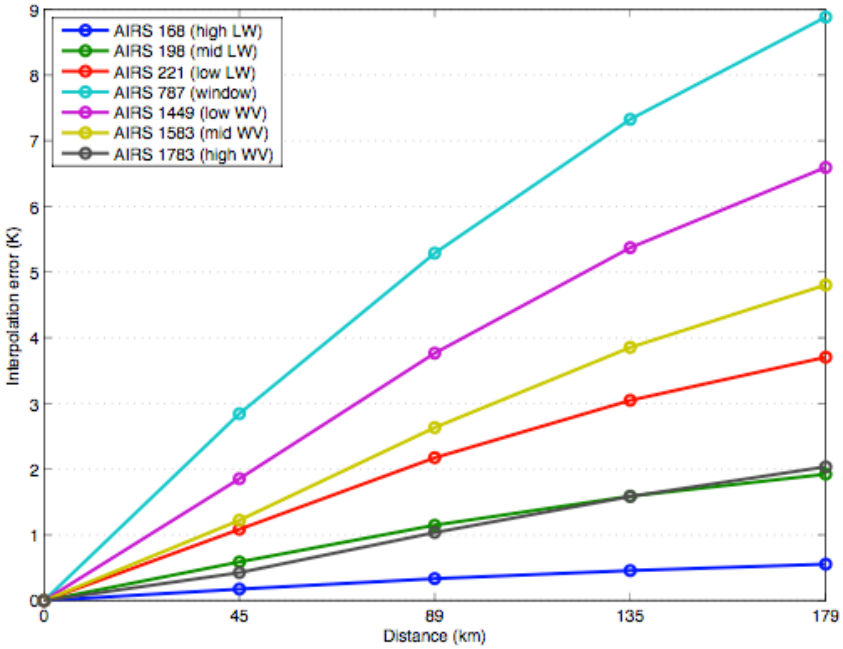
Background



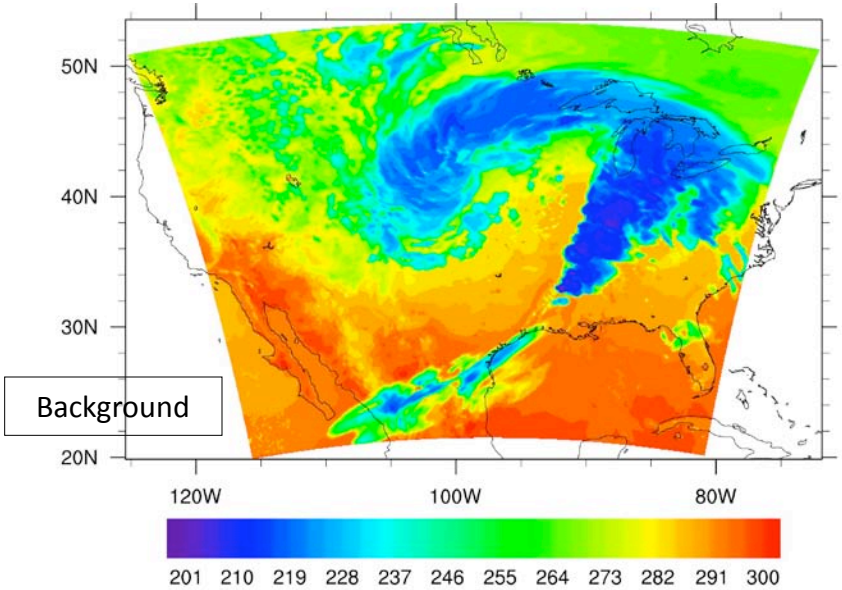
Innovations

Simulated mismatch in resolution:

- Perfect observations (high resolution)
- Perfect Background (lower resolution)

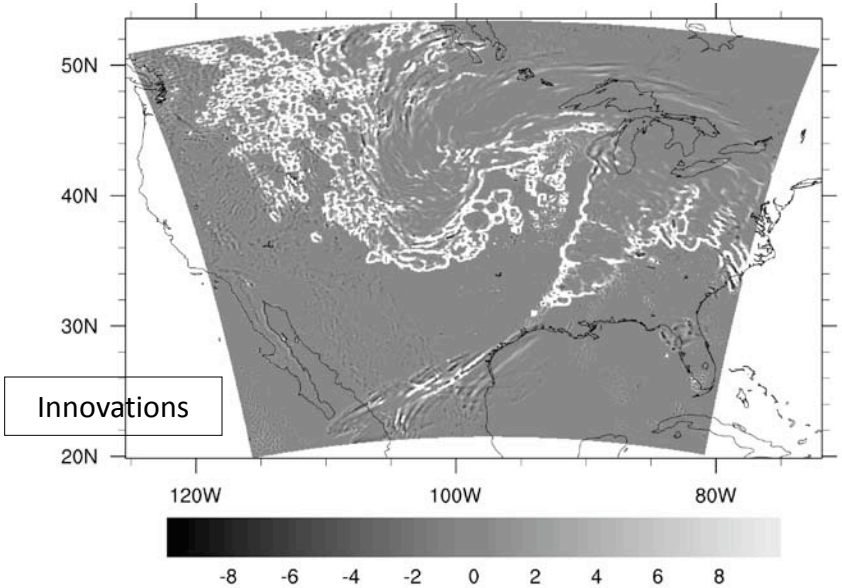


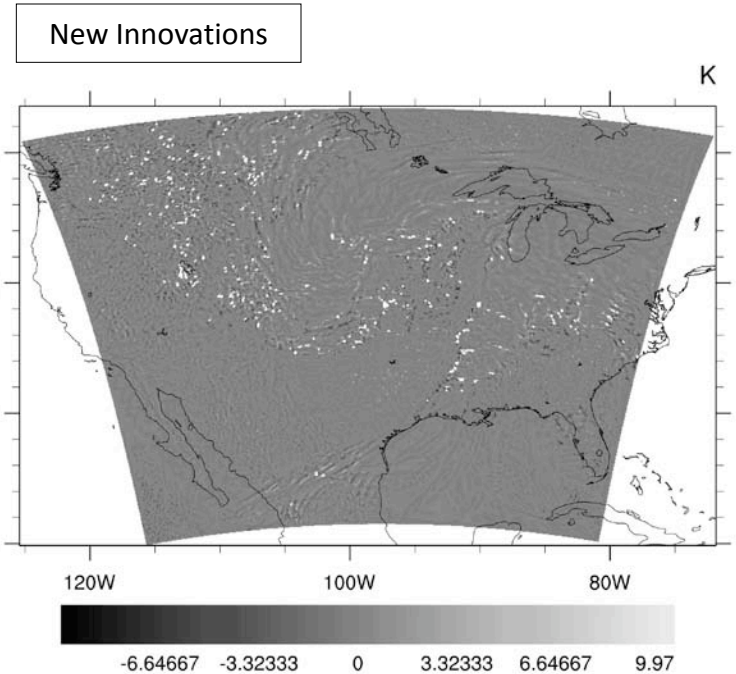
Representativeness Error



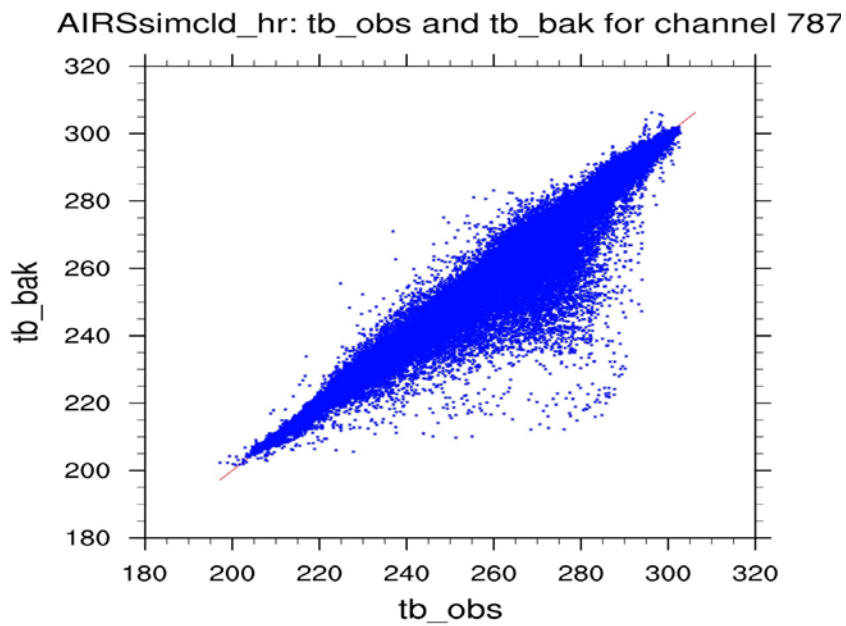
New interpolation scheme:

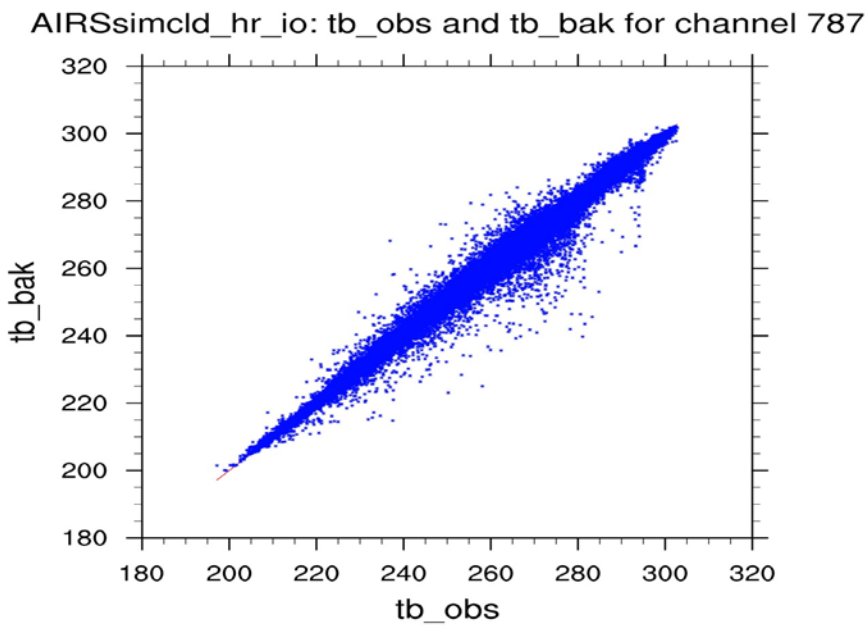
1. Automatic detection of sharp gradients
2. New “proximity” for interpolation



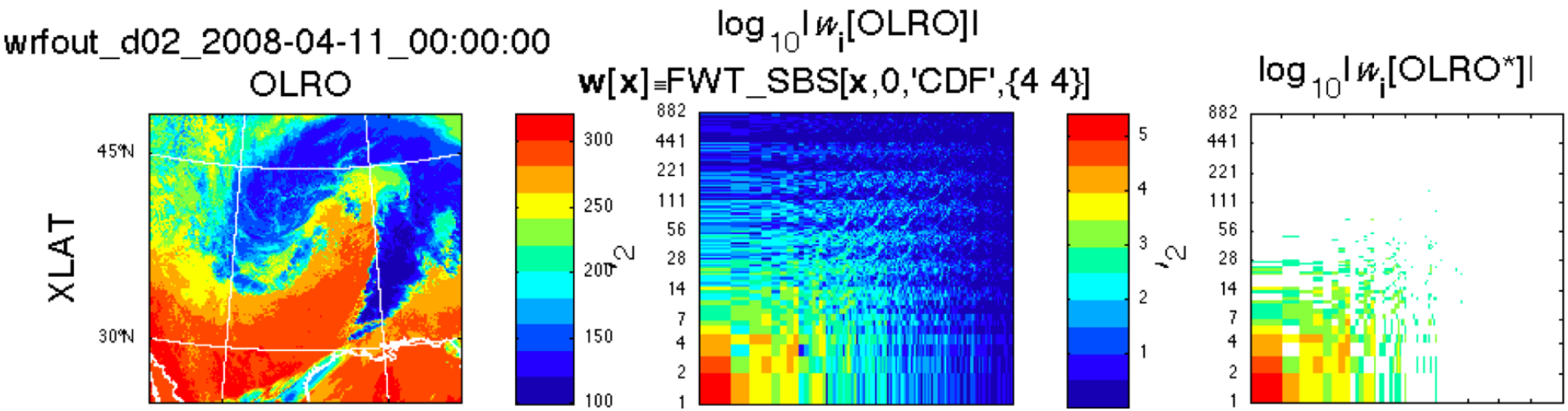


Representativeness Error



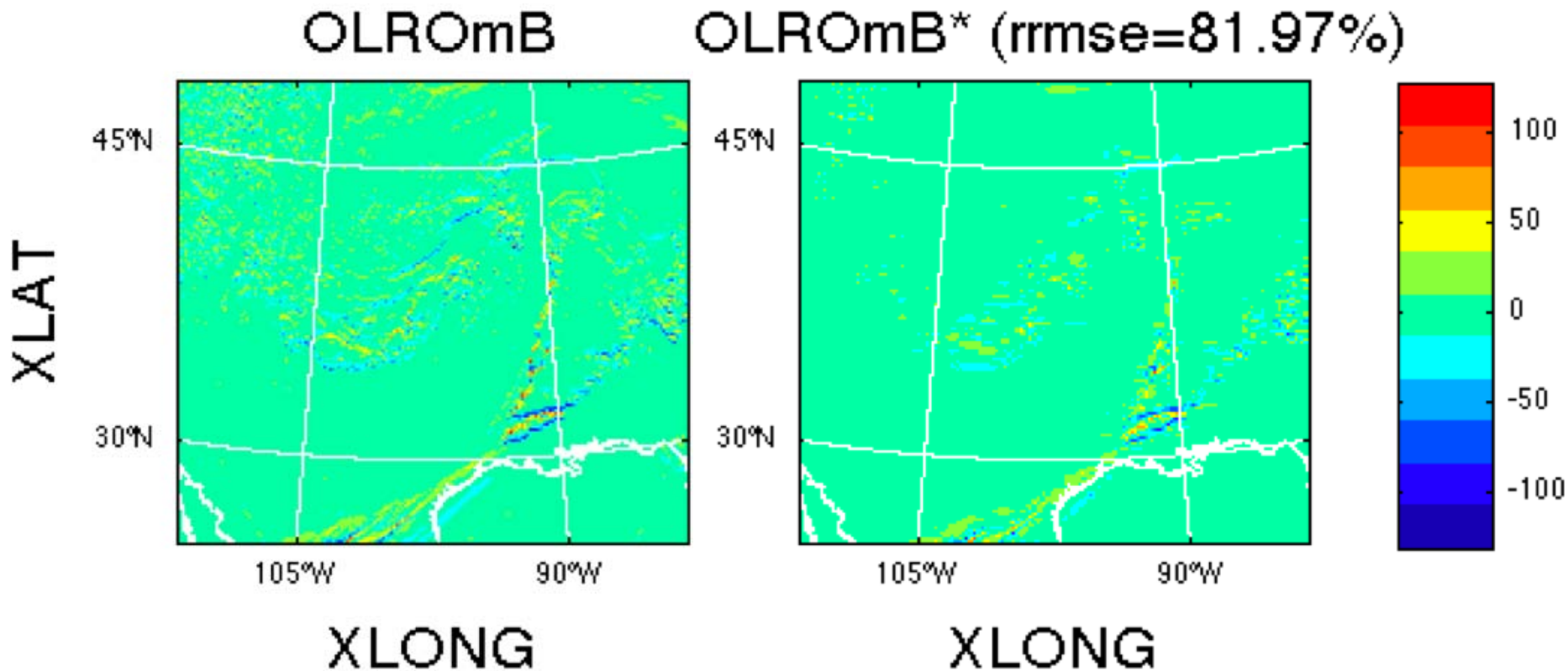


Isolate innovations scale-by-scale while preserving physical-space localization



By sorting and comparing $|w_i|$ (center) for obs. y_o (left) & background y_b we can isolate a multi-scale subset $i \in \mathbb{I}$ (right) from which *equivalent* representations y_o^* and y_b^* of y_o and y_b can be reconstructed…

Reduction in representativeness error

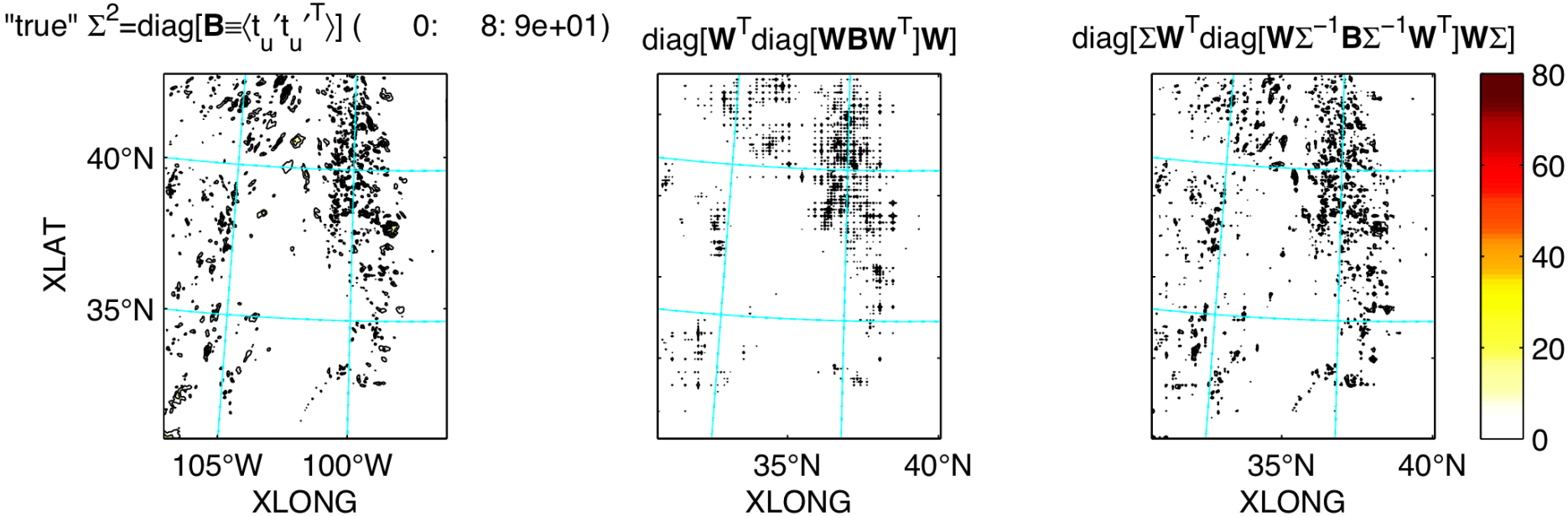


The raw $\boldsymbol{y}_o - \boldsymbol{y}_b$ (left) includes errors due to $\boldsymbol{y}_o$ and $\boldsymbol{y}_b$ coming from completely different representations, that (hypothetically) have been *reconciled* by the foregoing wavelet-coefficient selection procedure.

Inhomogeneous, flow-dependent background error covariances

Wavelet representation of Background Error Covariance Matrix

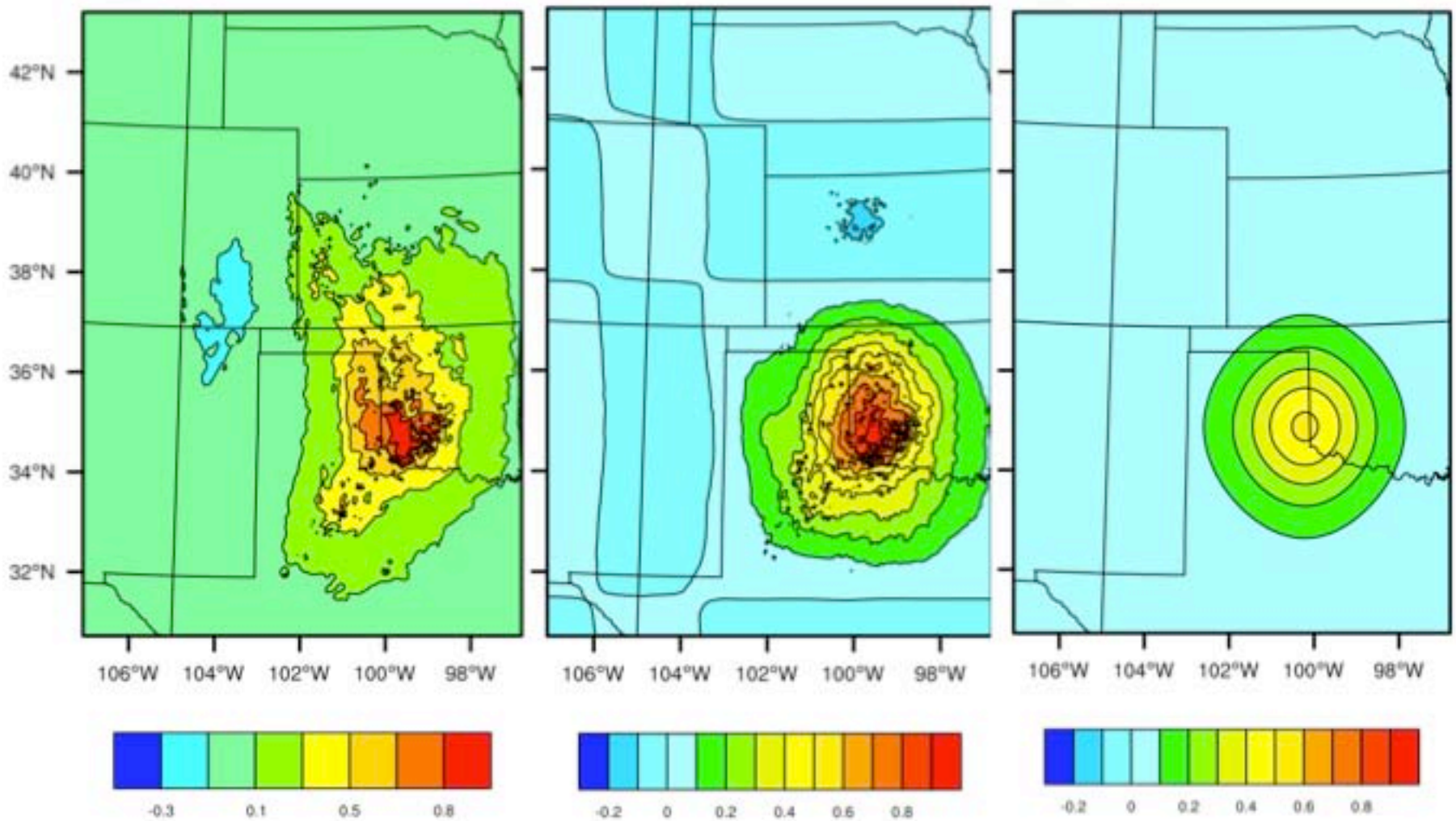
Background covariance can be *efficiently* modeled by assuming diagonality of the wavelet-coefficient covariance matrix (Fisher & Andersson, Deckmyn & Berre).



•The normalization with $\mathbf{\Sigma}^2$ = diag **B** (left) yields a model with *fewer* artifacts (right) than does $\mathbf{\Sigma}$ = **I** (center) (as found by D&B earlier).

• In these plots **x** is unbalanced temperature anomaly in a 30-member ensemble computed by Dowell with horizontal resolution N = 450×350.

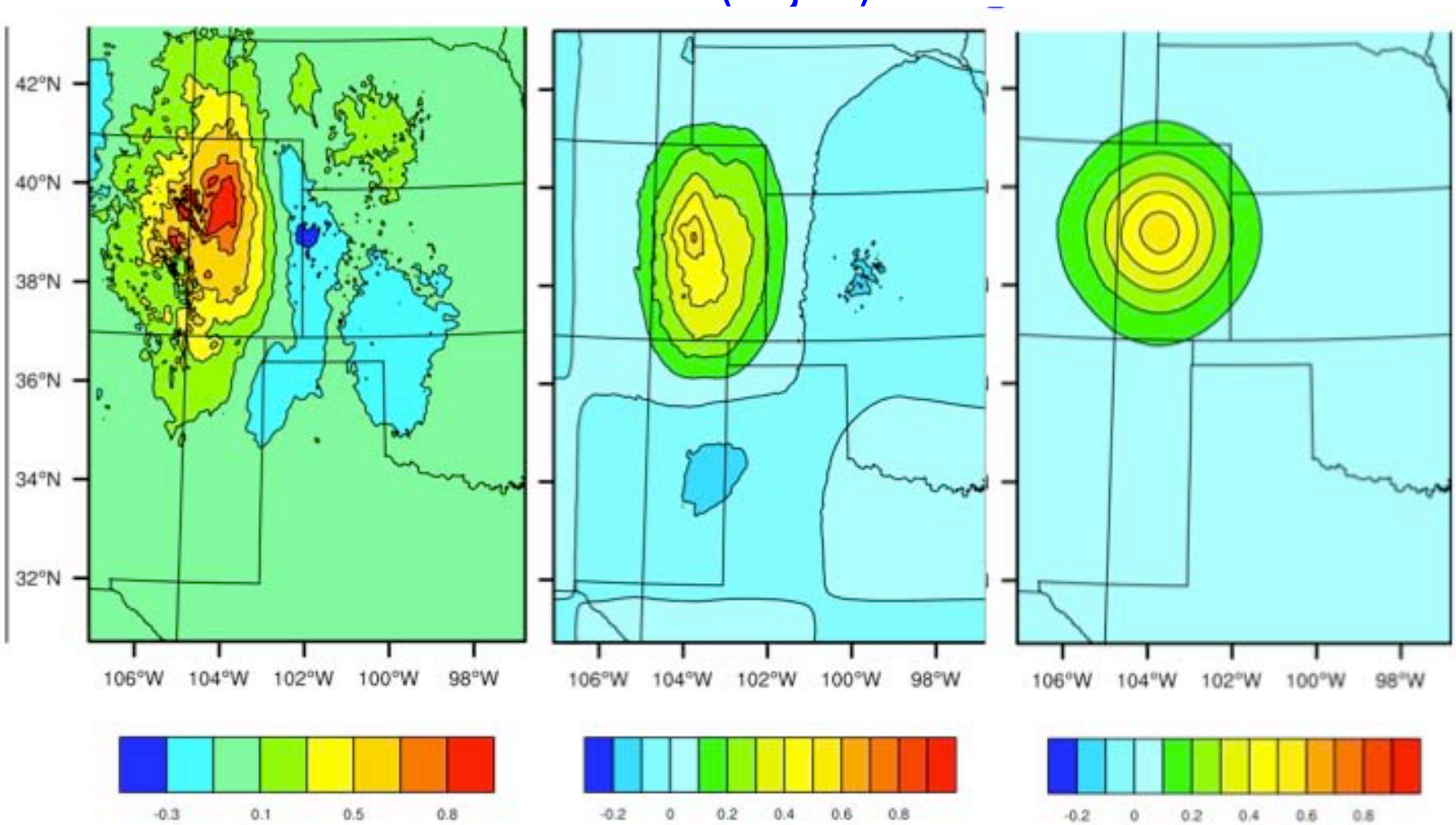
New **B** (center, 7C30 wavelet) represents heterogeneity (left, ensemble), unlike homogeneous recursive filters (right).



from an E = 30-member N = 351×451, 5-level dataset.

• Note that the wavelets represent some multi-scale anisotropic features such as the SW-NE structures over N Texas.

Wavelet **B** model (center) captures anisotropy (left), unlike recursive filters (right).



- Response to an observation at $\lambda=-104°$, $\varphi=39°$, $\eta=0.28$.
- The *overall* horizontal scale is an adjustable parameter len_scaling=0.9 (for RF), nb=7 (for wavelets) and alpha_corr_scale=200km (for ensemble), each of which has only been roughly calibrated.

Geographical mask

- Use vertical sum of background precipitation (no smoothing yet)
- Differentiate clear, light and heavy rain classes
- Compute different **B** statistics in each rain class

Definition

- Clear $q_{\text{rain}}^{1,2} \leq 10^{-3}$ g/kg
- Mixed
- Light Rain $q_{\text{rain}}^{1,2} \geq 10^{-3}$ g/kg and $q_{\text{rain}}^{1,2} \leq 10^{-1}$ g/kg
- Heavy Rain $q_{\text{rain}}^{1,2} \geq 10^{-1}$ g/kg

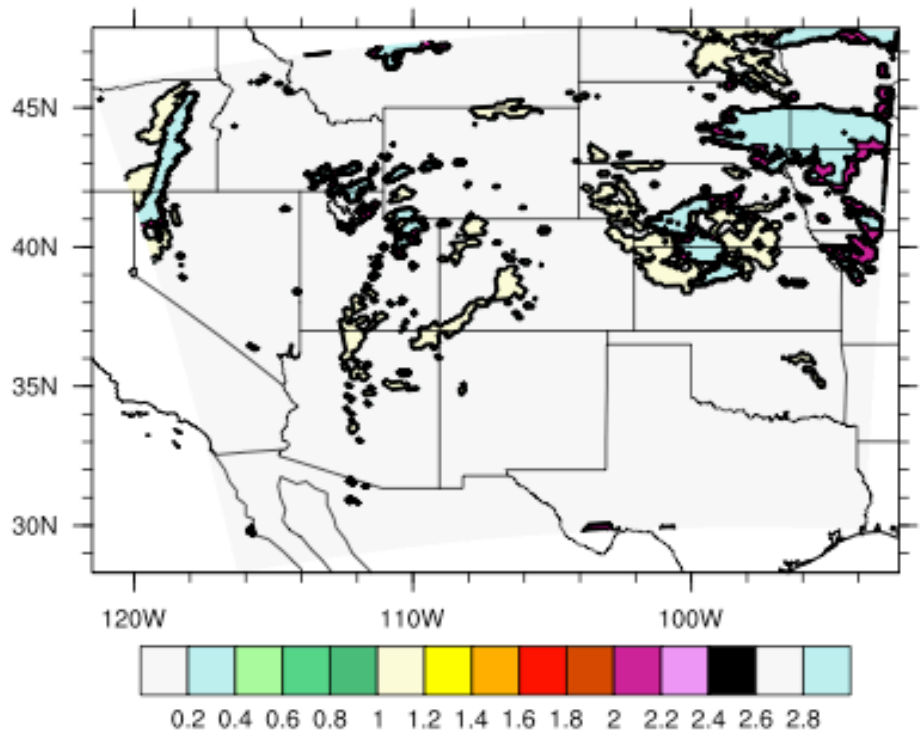
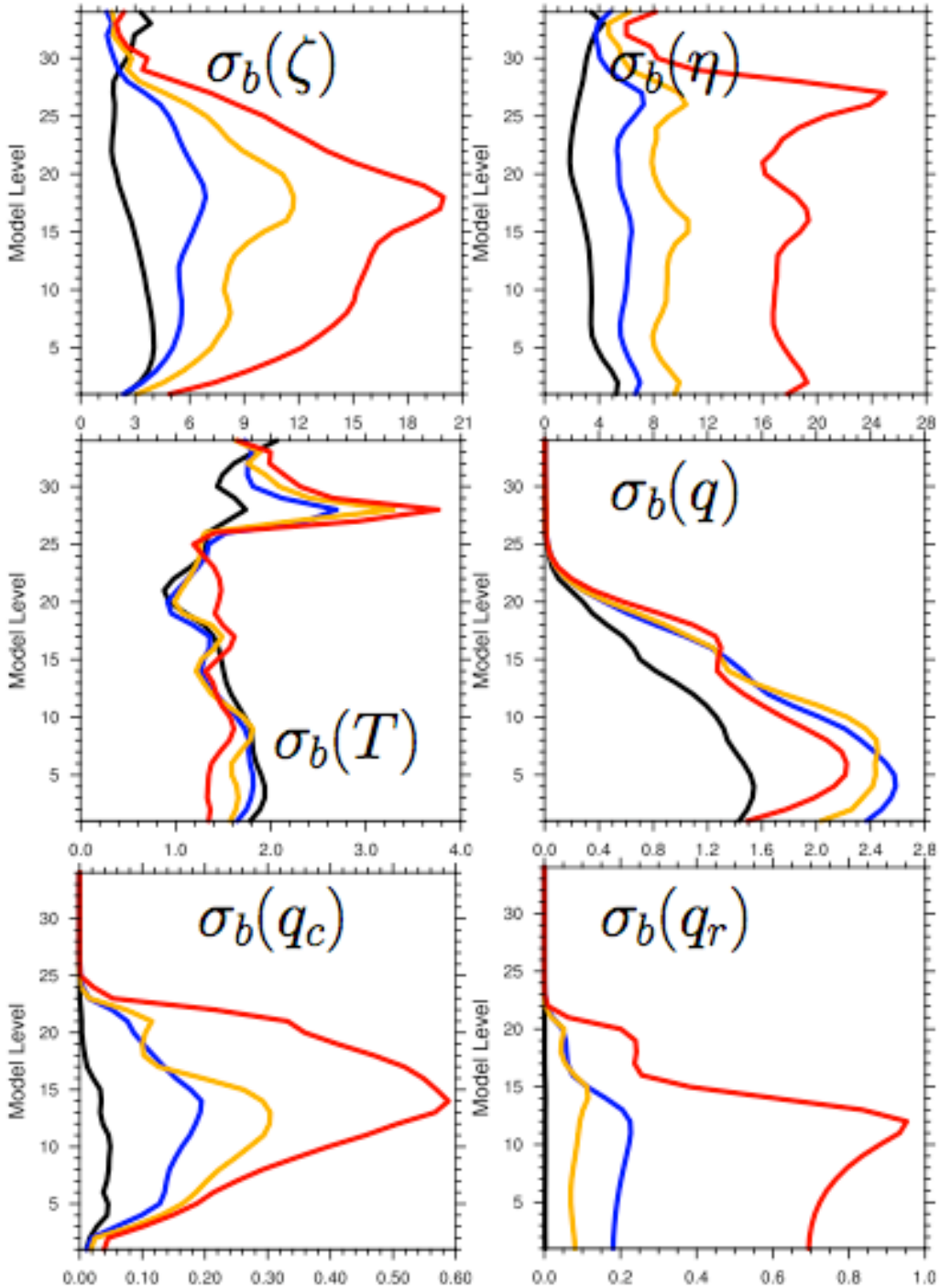
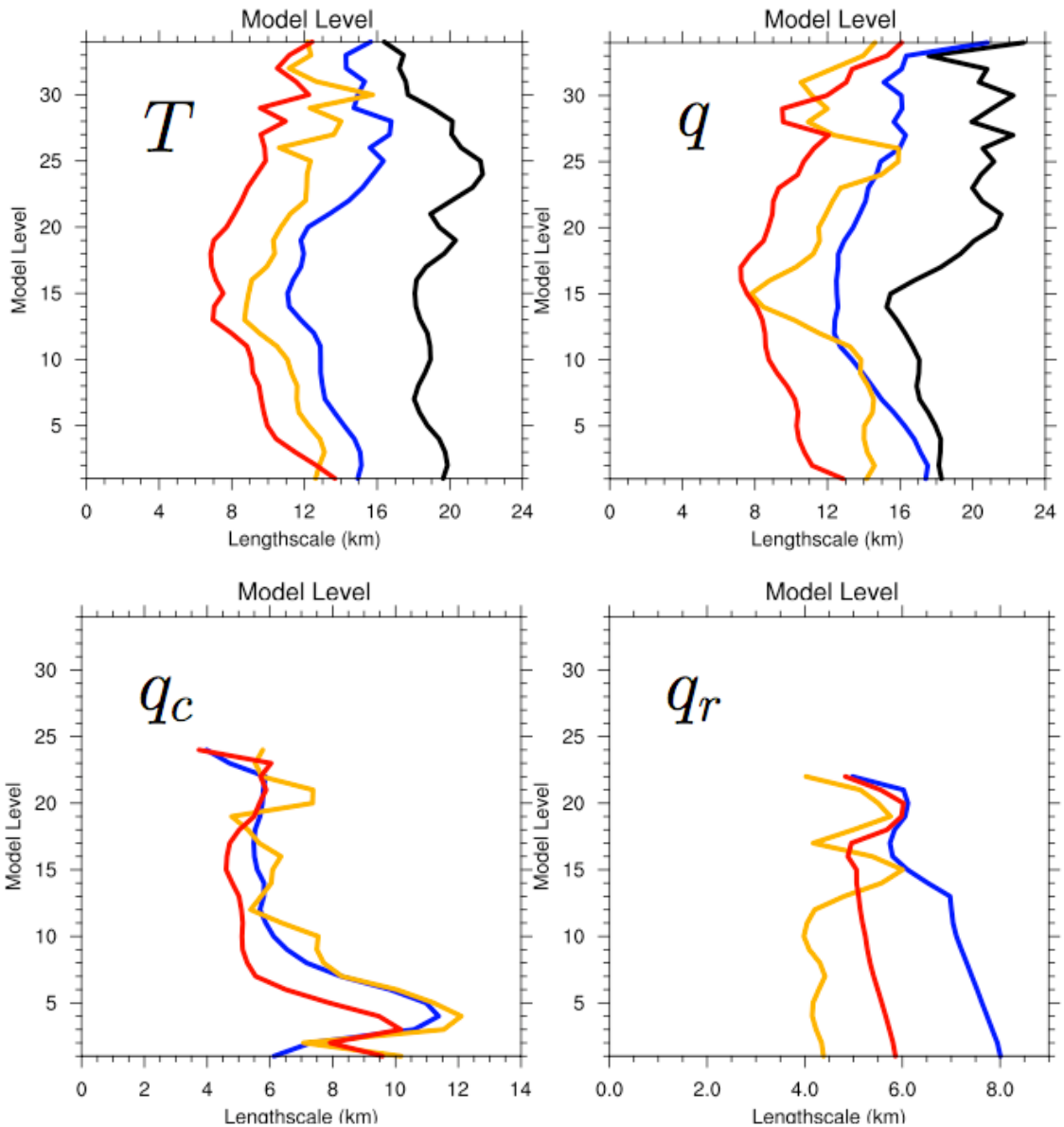


Figure: Rain Class on 07-10-2009

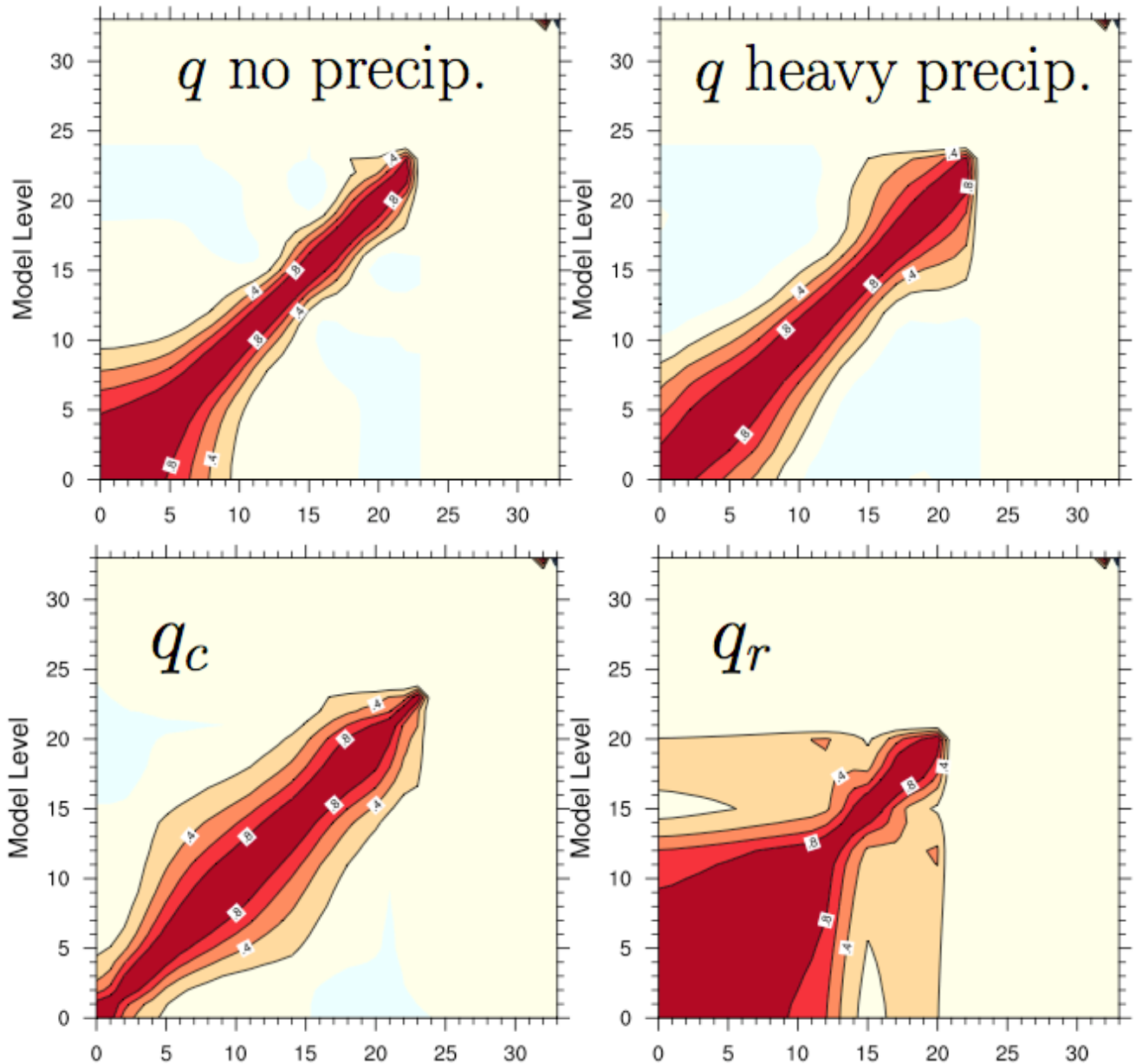
Standard Deviations



Horizontal Lengthscales



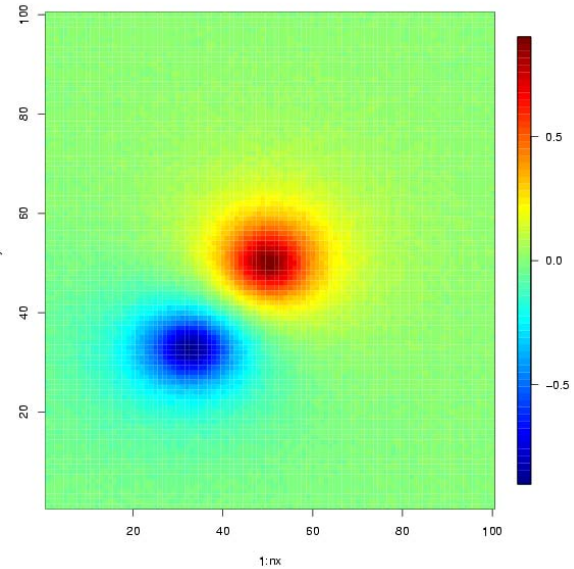
Vertical Correlations

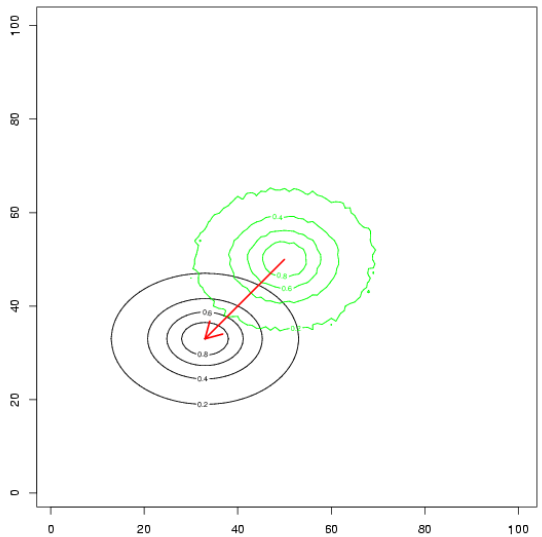


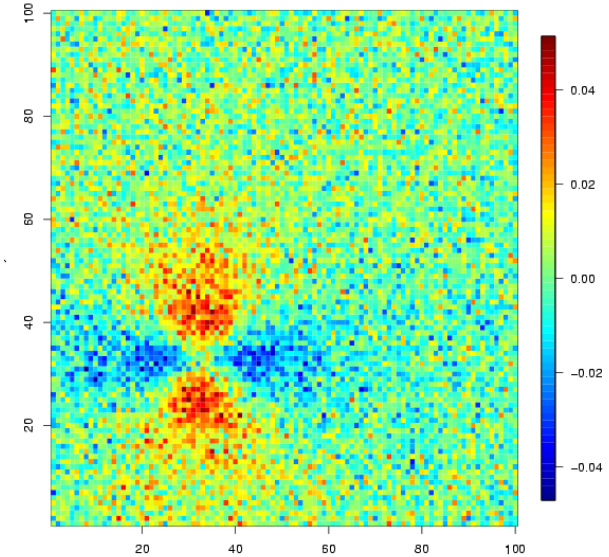
Displacement Analysis

Displacement, Field Alignment, Morphing Analysis, …

background error => displacements of coherent features + additive (residual) error







Tikhonov Regularization constraints

Smoothness

$$J = J_b + J_o\left(y^{obs}, X^{bg}, \delta x, \delta y\right) + J_d\left(\delta x, \delta y\right)$$

- Extend the control variable to include displacement "d "
- Add smoothness constraint J_d on d to avoid over-fitting

Tikhonov Constraints

- Field penalization $J_{L2} = ||d||^2$
- Gradient penalization $J_{Grad} = ||\nabla d||^2$
- Divergence penalization $J_{div} = ||\nabla \cdot d||^2$
- Laplacian penalization $J_{lap} = ||\Delta d||^2$

Bayesian Interpretation

- In the DA framework, $J_d = x^T D^{-1} x$ where D is the covariance of displacement errors.
- For a few specific cases, it is possible to derive equivalent Tikhonov regularizations from D and D^{-1} (Tarantola 2005).
- For instance, exponential covariance is 1st order regularization (= field + gradient penalization)

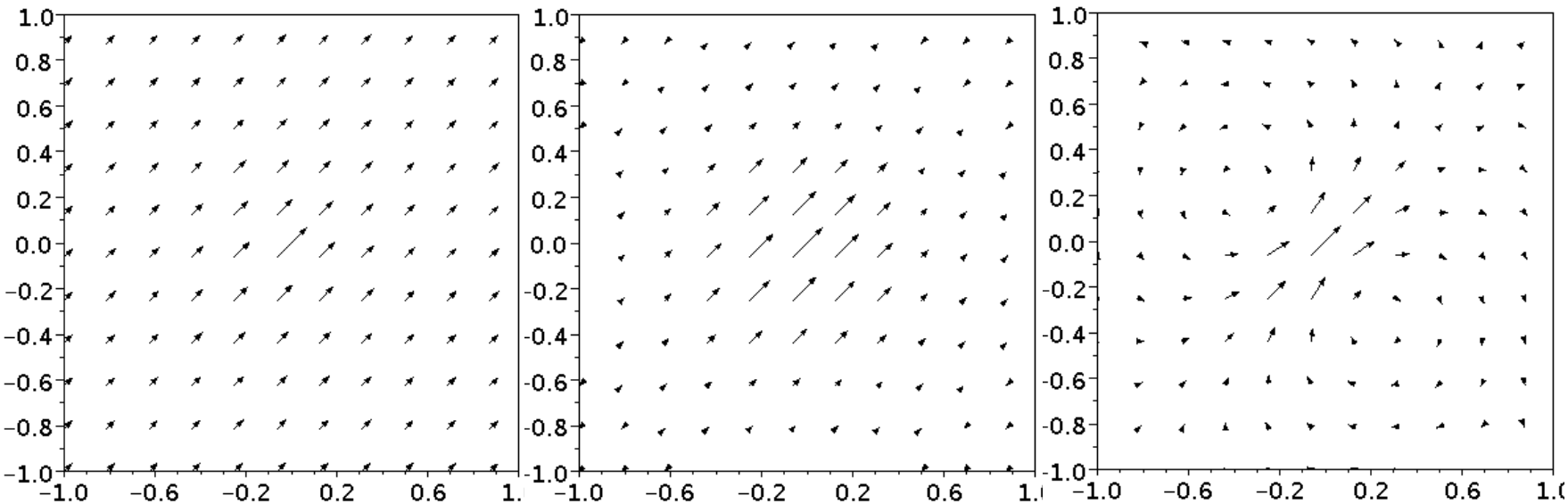
Courtesy Yann MICHEL, Meteo-France

A numerical test

Displacement "single obs test"

$$\mathrm{Min}_d\ J(d) = J_o + J_d$$

- Jo is the observation of a displacement y_d=[1,1] at the center
- Use of conjugate-gradient algorithm (quadratic constraints)
- Study the effect of Tikhonov regularizations on analyzed displacement



L2 + Gradient

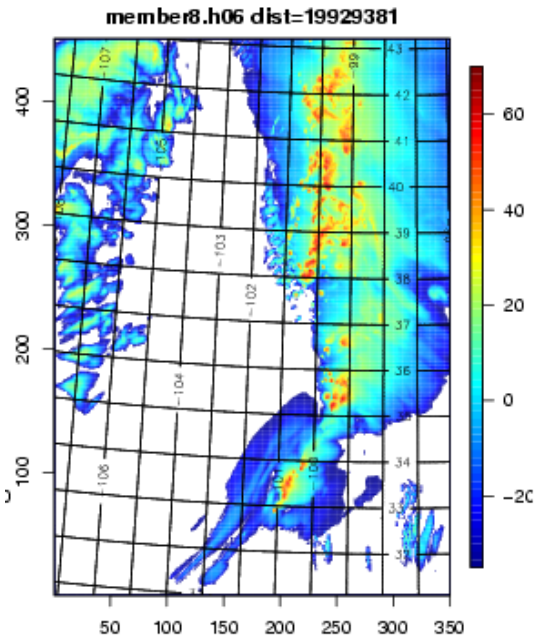
L2 + Laplacian

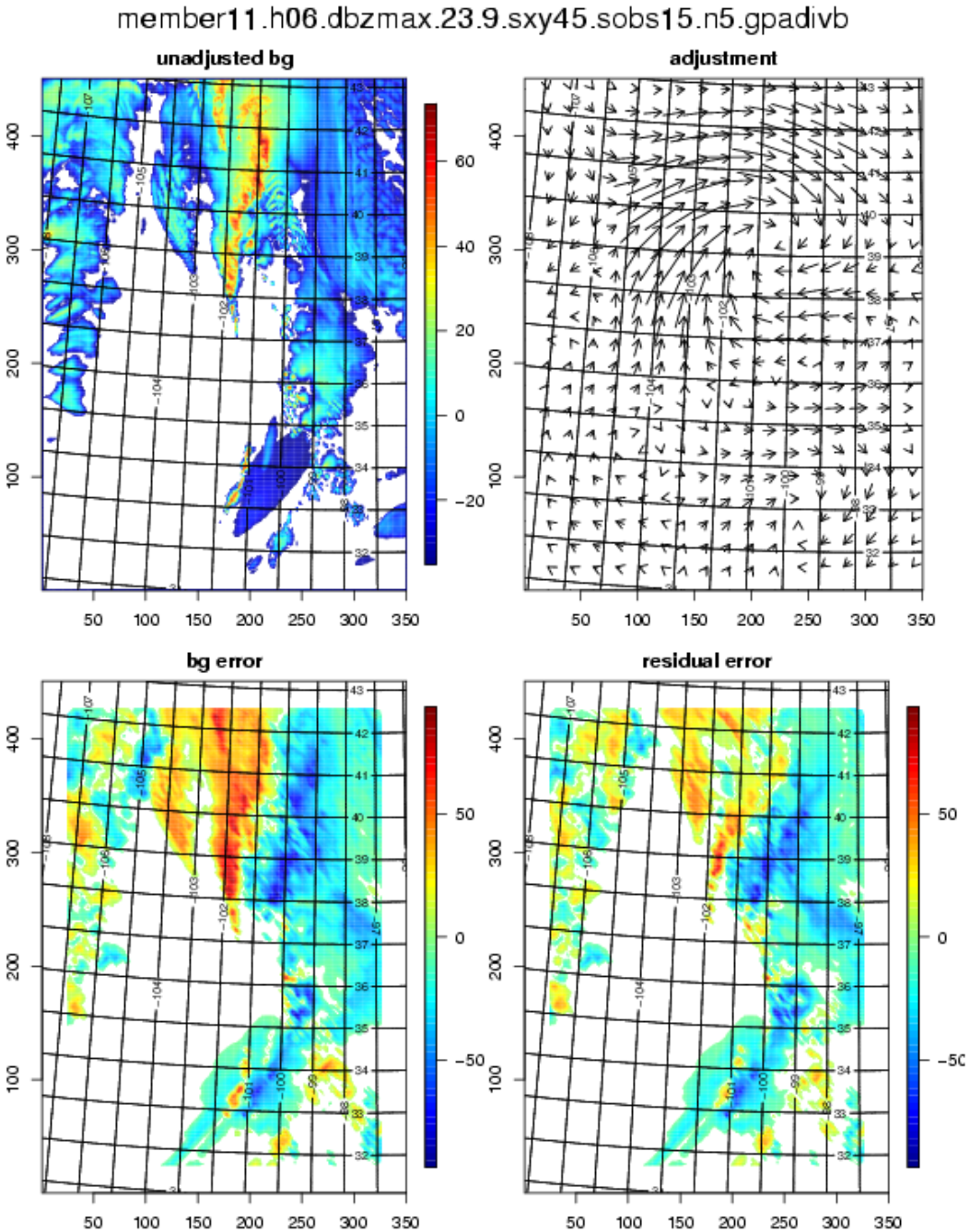
L2 + Divergence + Laplacian

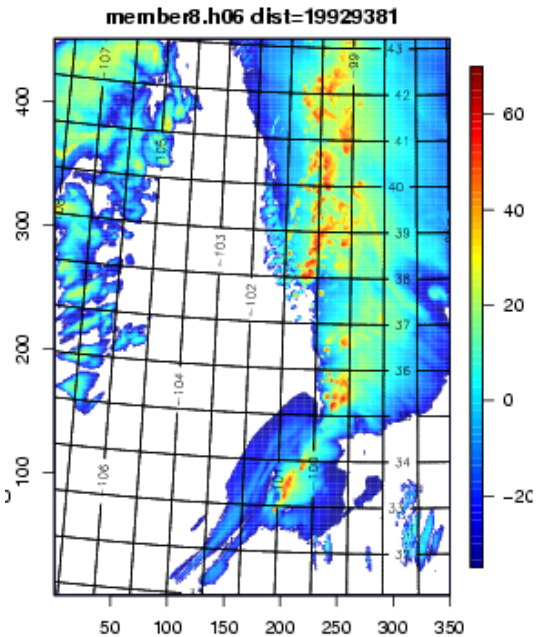
Courtesy Yann MICHEL, Meteo-France

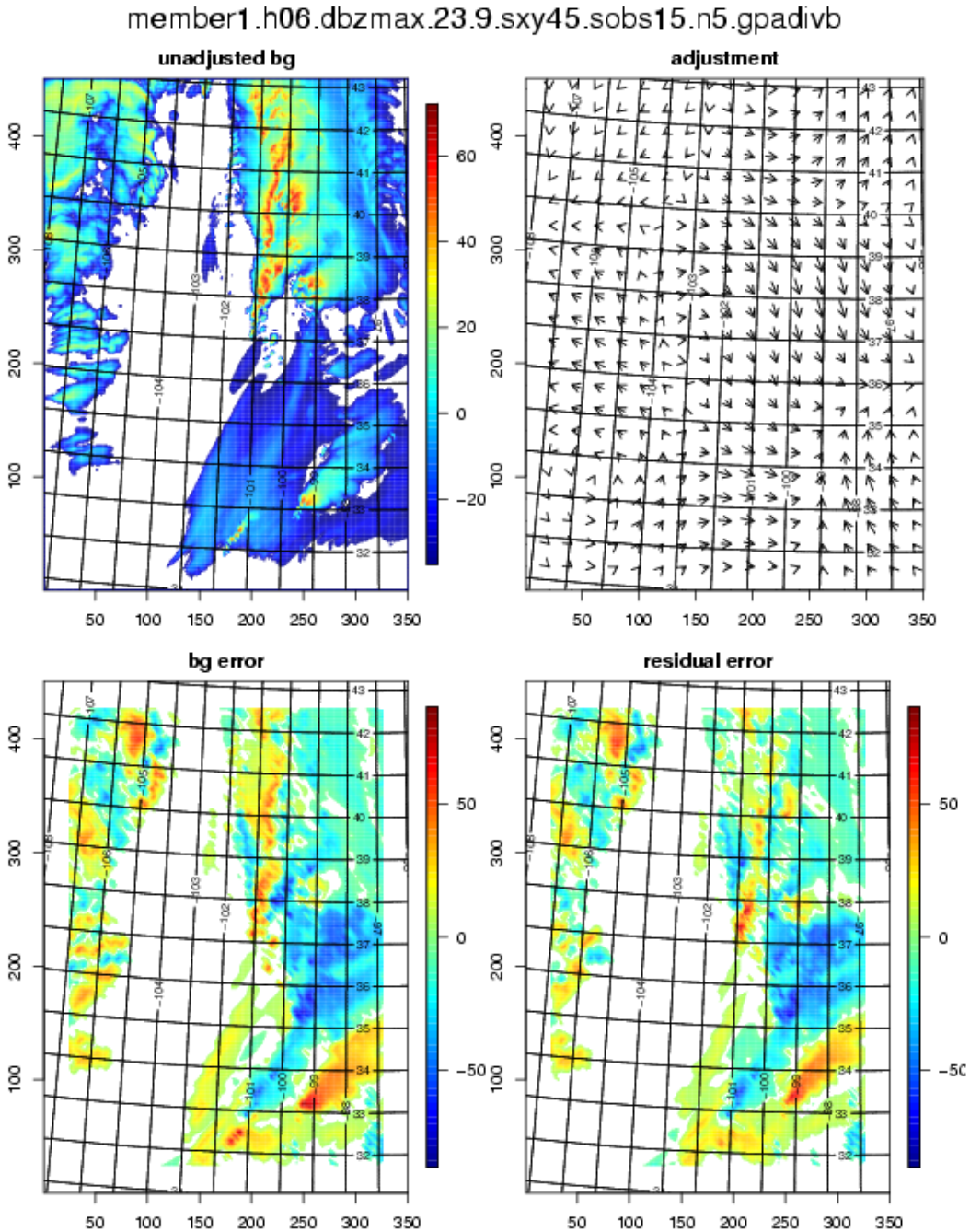
- **penalty function J_{pen} constrains**
  - maximum size of displacements (“barrier”)
  - mean square size of displacements
  - noisiness of displacement field (Laplacian)
  - divergence of displacement field

- **Implementation details**
  - use truncated spectral representation of displacements
  - use nonlinear optimization software
  - use adjoint to compute gradient of J


member8.h06 dist=19929381


member11.h06.dbzmax.23.9.sxy45.sobs15.n5.gpadivb
unadjusted bg
adjustment
bg error
residual error


member8.h06 dist=19929381


member1.h06.dbzmax.23.9.sxy45.sobs15.n5.gpadivb
unadjusted bg
adjustment
bg error
residual error

Conclusions

- Cloud 3D structure is usually under-observed → rely on covariances (climatology or ensemble) to partition information and model to propagate in time
- For IR sounders, simple linear observation operator = better first guess to get closer to linear regime
- Observations and background usually at different scales: large representativeness error for cloudy radiances

Conclusions

- Need to improve the background error covariances for inhomogeneous, flow depend signal (GEN_BE package)
- Displacement analysis shows great potential for clouds
- Start with regional prototype, based on WRF model
- Evolve to global system, based on MPAS model

Thank you for your attention…