Assimilation of cloud/precipitation data at regional scales

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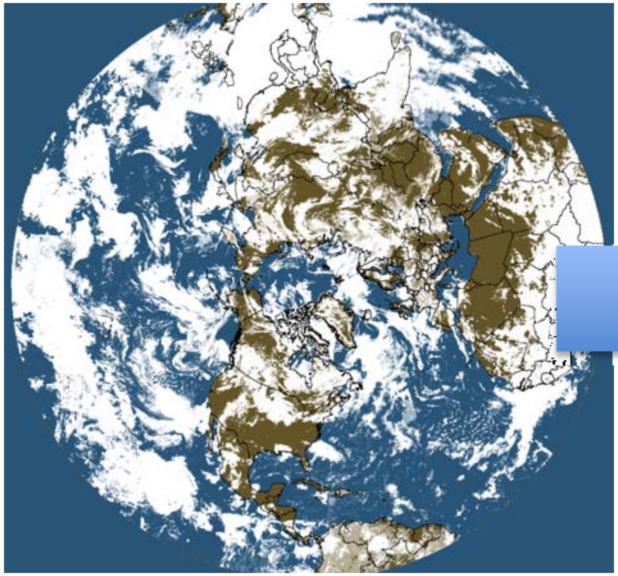
Introduction

- **The Model**
  - Weather Research and Forecasting (WRF) community model.
  - Advanced Research WRF (ARW) non-hydrostatic dynamical core
- **The Data Assimilation (DA)**
  - Data Assimilation Research Testbed (DART): EnKF
  - WRF Data Assimilation (WRFDA): 3DVar, FGAT, 4DVar
  - Gridpoint Statistical Interpolation (GSI): 3DVar, 4DVar under development
- **The Operational Applications**
  - Air Force Weather Agency (AFWA)
  - NOAA ("Rapid Refresh")

Introduction

World-
Wide
Merged
Cloud
Analysis



AFWA Coupled Analysis and Prediction System (ACAPS)

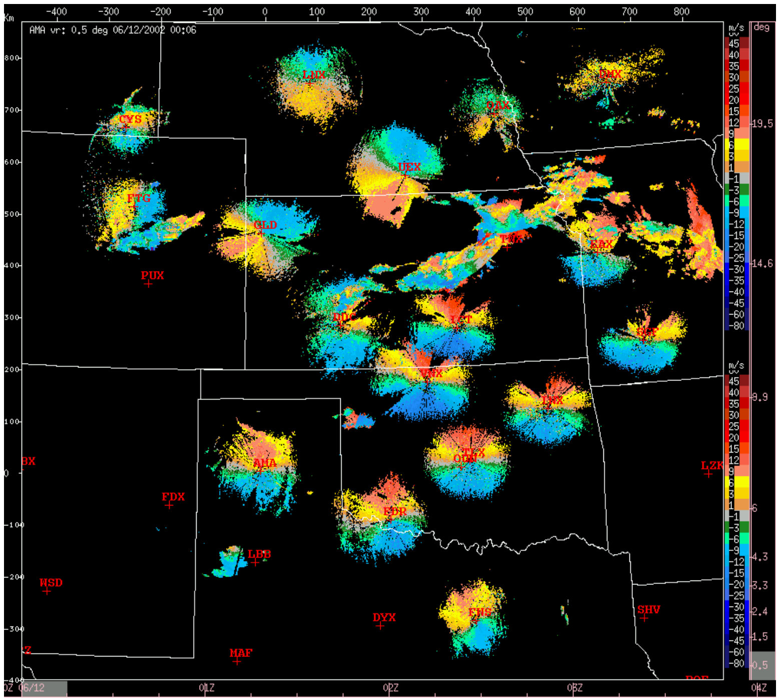
***<u>SCOPE</u>**: Develop an analysis and prediction system of 3D cloud properties combined with the dynamical variables.*

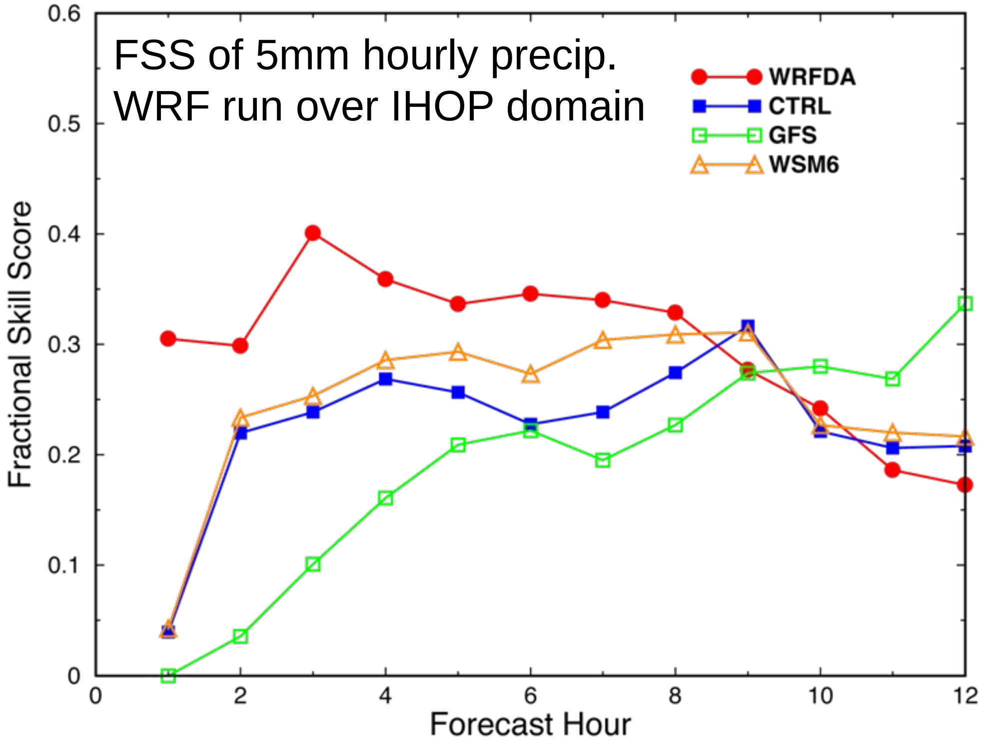
WRFDA 3DVAR and radar radial velocity

IHOP one-week retrospective study

CTRL	Initialization by NCEP ETA analysis
GFS	Initialization by NCEP GFS analysis
WRFDA	WRF 3DVAR radar radial velocity
WSM	CTRL with different microphysics

Radial velocity 2002061200 UTC



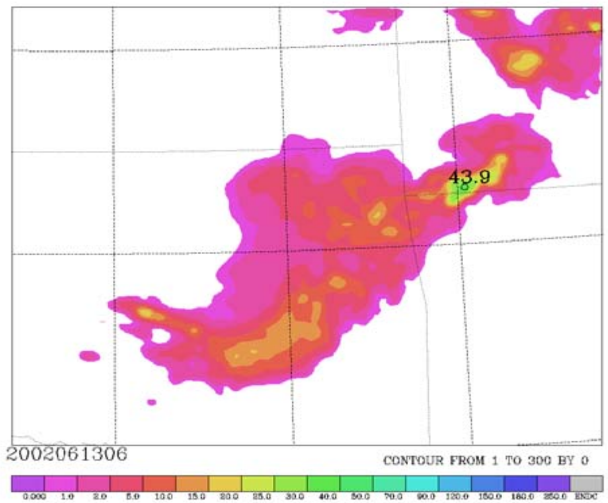


- Radar data assimilation improves the precipitation forecast up to 8 hours
- Forecast is more sensitive WRT initial conditions than physics (microphysics is most sensitive among all physics tested)

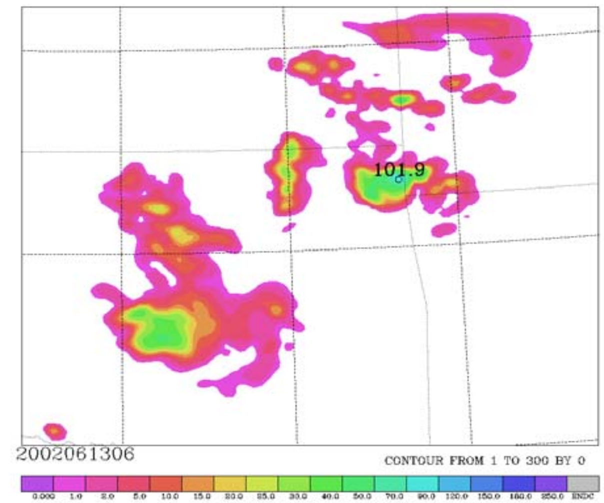
(Jenny Sun)

Hourly precipitation at 0600 UTC 13 June

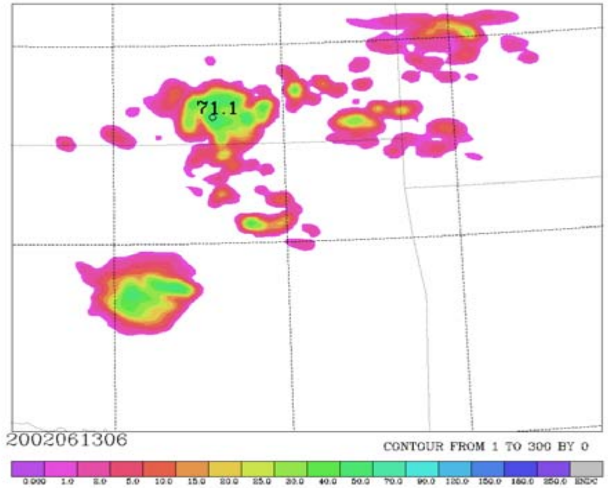
OBS



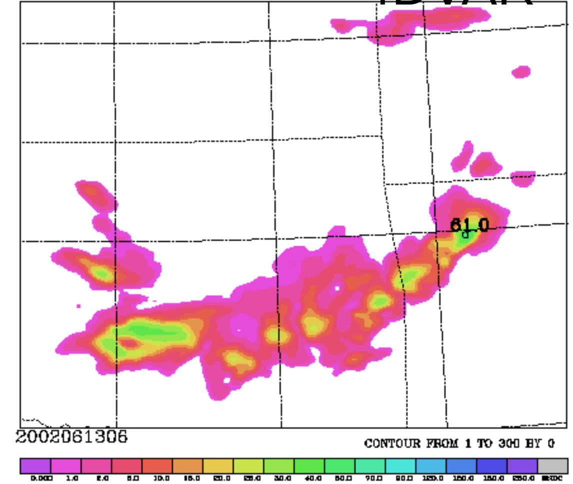
GFS



3DVAR

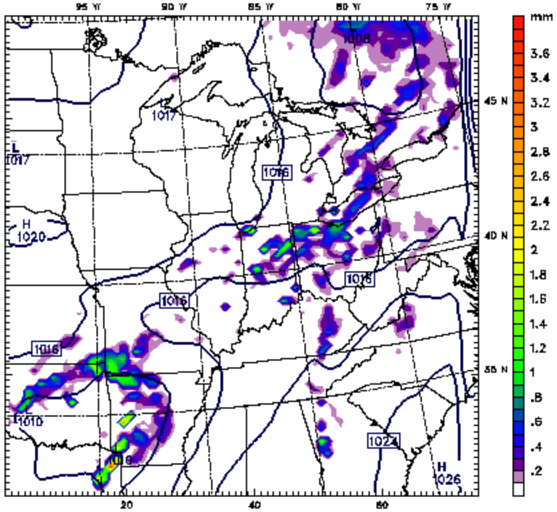


4DVAR

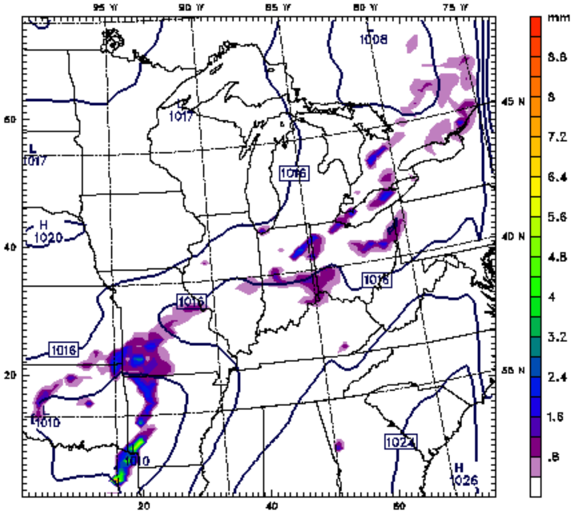


Simulated SSMIS radiances

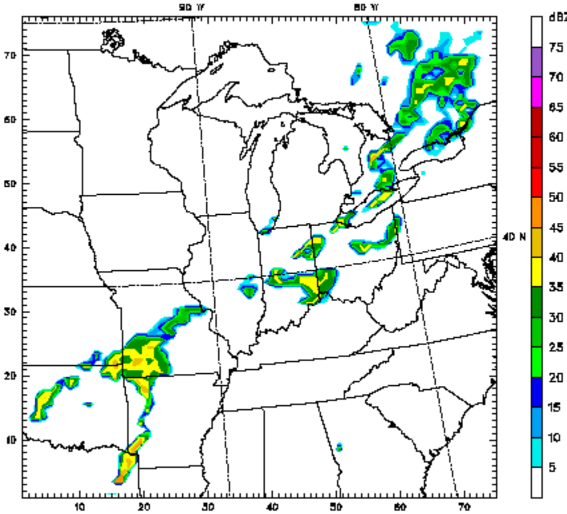
Column-Integrated cloud water



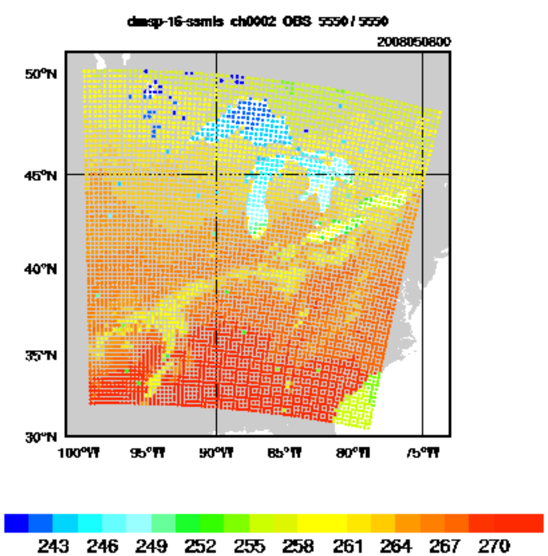
Column-Integrated rain water



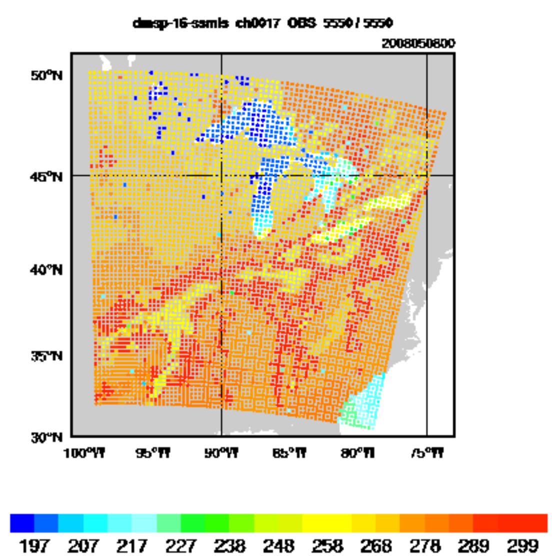
Radar Reflectivity



Simulated Ch2 Tbs



Simulated Ch17 Tbs



Model = “truth” for SSMI/S radiance simulation

Only liquid hydrometeors considered

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

(Zhiquan Liu)

Assimilation of simulated SSMIS radiances in WRF 3DVAR

- Use total water $\mathbf{Q_t=Q_{wv}+Q_{clw}+Q_{rain}}$ as a control variable (instead of individual hydrometeors)
- 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

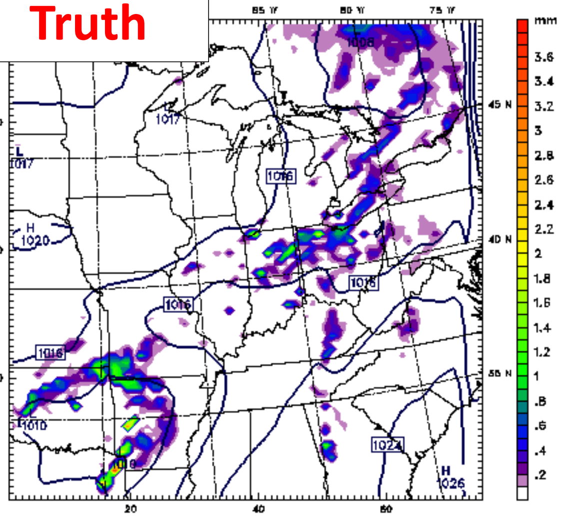
- Minimization starts from a cloud-free background, this scenario can be realistic for less accurate cloud/precip. forecast in the real world

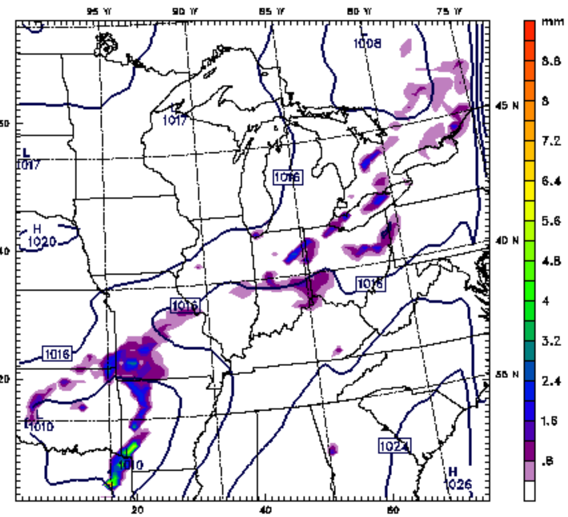
- Perfect background for other variables (T,Q etc.)
- Perfect observations (no noise added to the simulated Tbs)

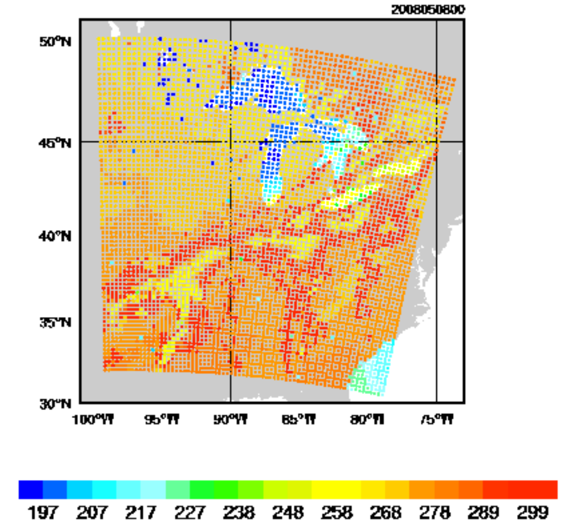
- 2 outer-loops

Simulated SSMIS radiances

Truth

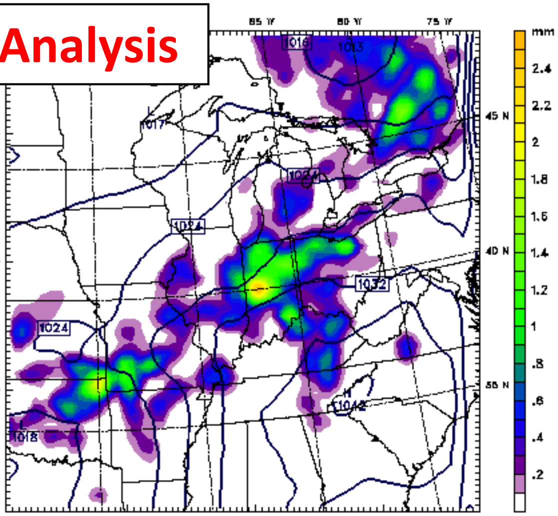


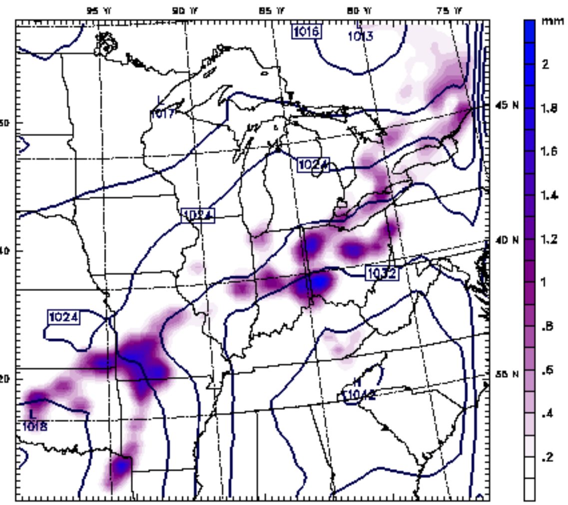


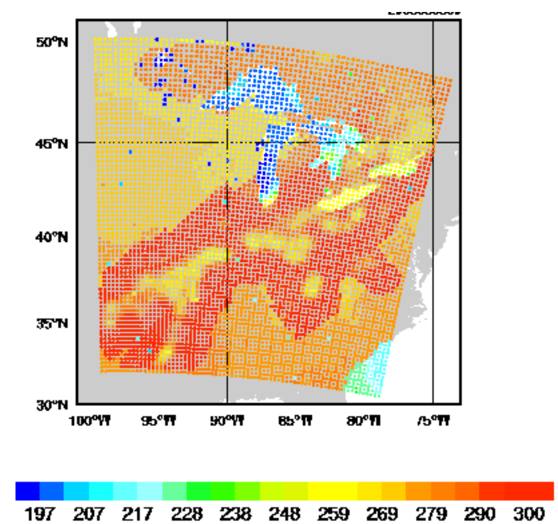


Column-Integrated cloud water **Column-Integrated rain water** **SSMIS Channel 17**

Analysis





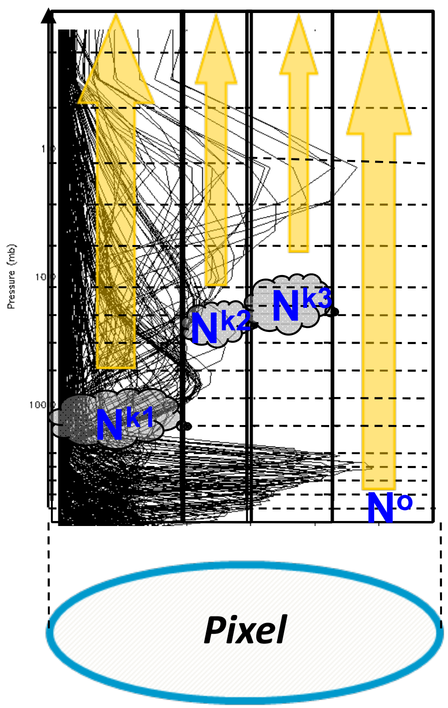


Infrared Cloudy Radiances

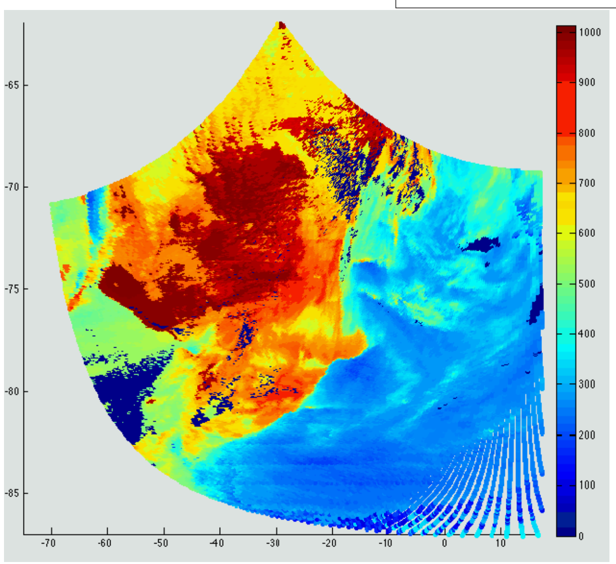
$$R_\nu^{Cld} = N^{o} R_\nu^{o} + \sum_{k=1}^{n} N^{k} R_\nu^{\bullet k}$$

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

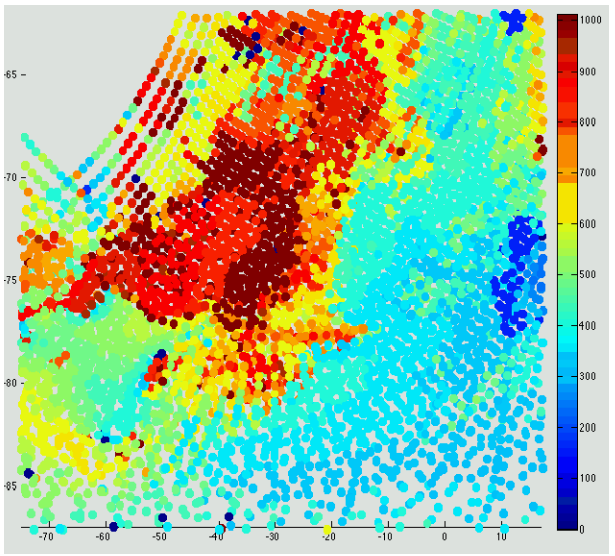
$$J(N) = \frac{1}{2}\sum_{\nu}\left(\frac{R_\nu^{Cld} - R_\nu^{Obs}}{R_\nu^{\circ}}\right)^2 \quad \text{with} \quad \begin{cases} 0 \le N^k \le 1, \forall k \in [0, n] \\ N^{\circ} + \sum_{k=1}^{n} N^k = 1 \end{cases}$$



Cloud Top Pressure (hPa)



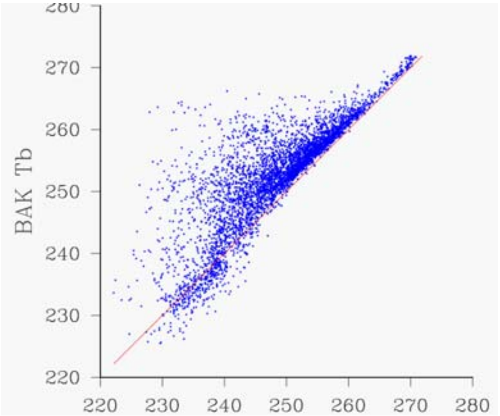
MODIS Level2

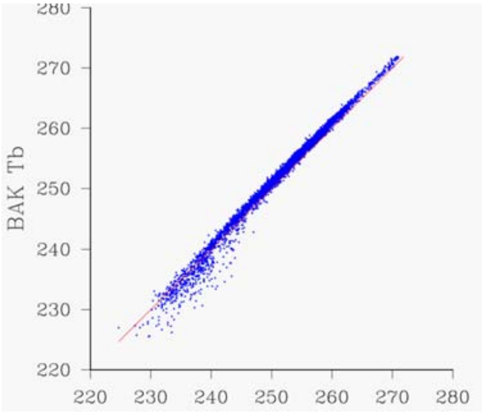


AIRS MMR

IR Cloudy Radiances

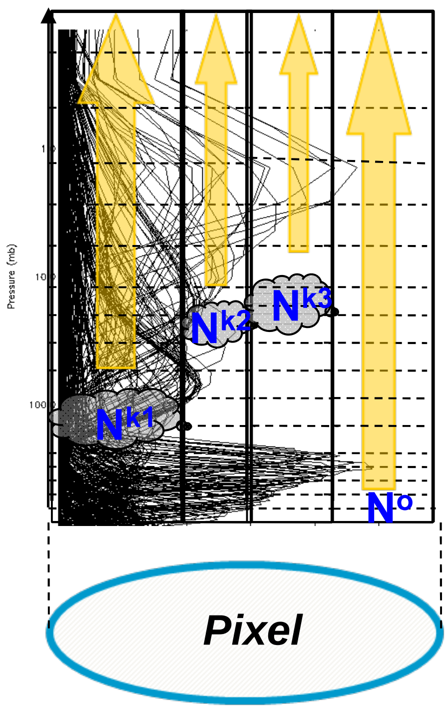
(linear obs operator)

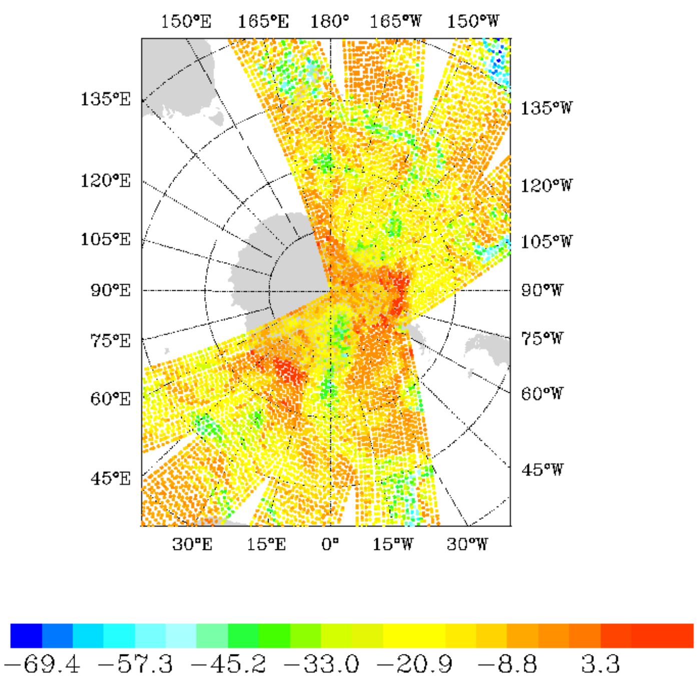


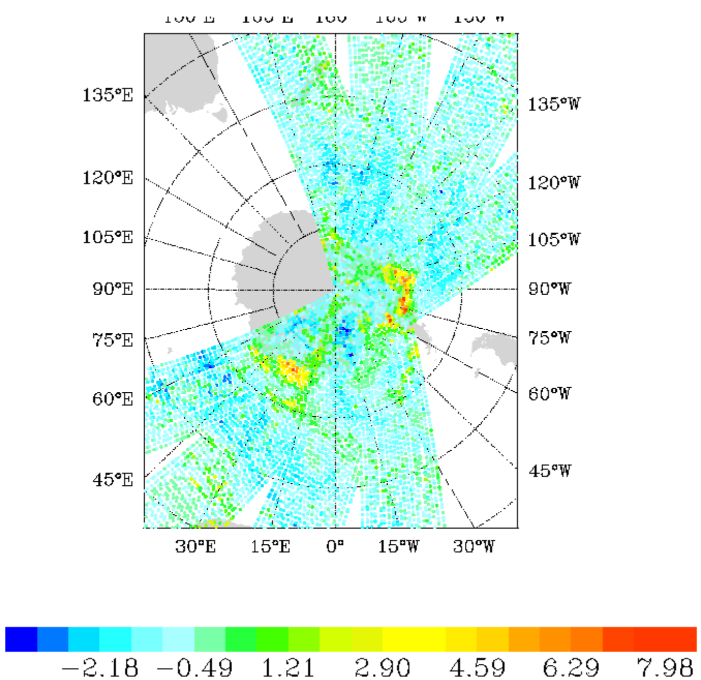


$$R_\nu^{Obs} - R_\nu^{o}$$

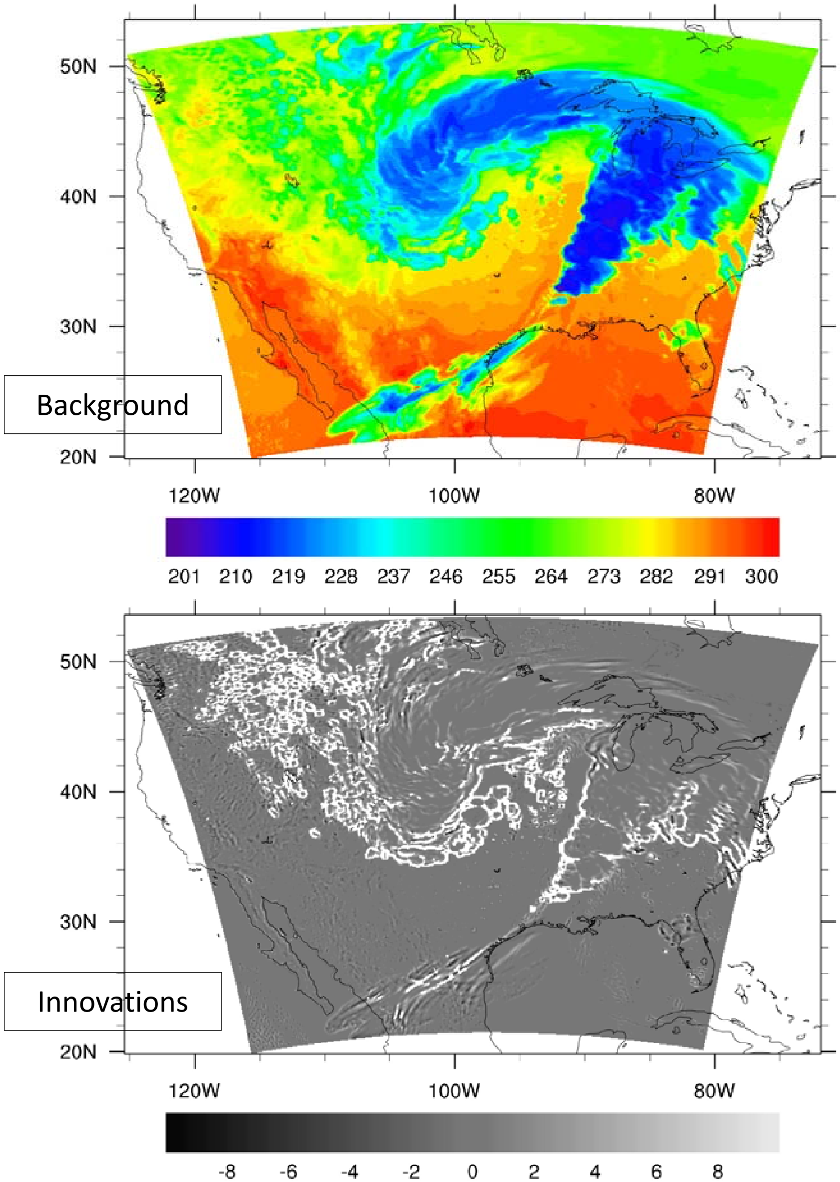
$$R_\nu^{Obs} - R_\nu^{Cld}$$





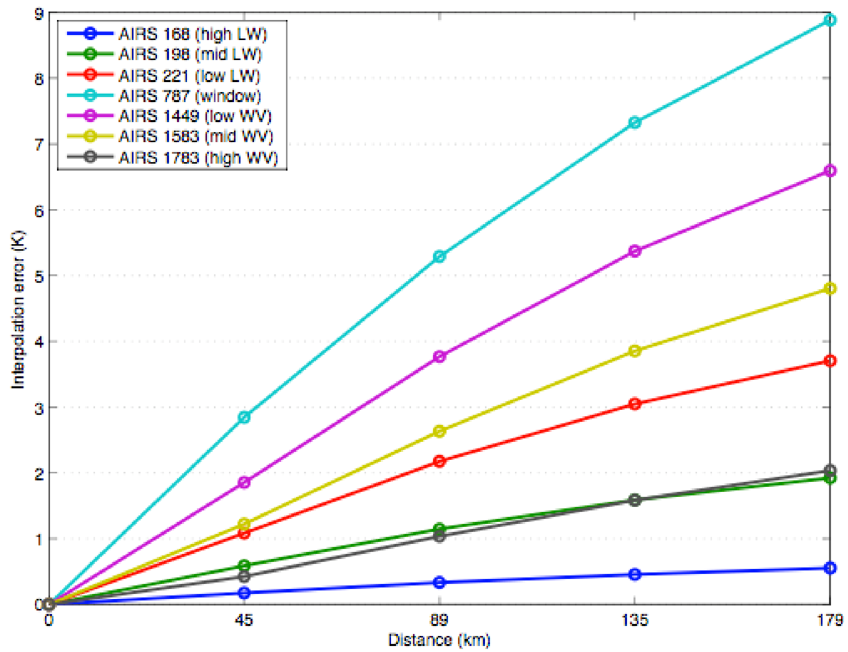


Representativeness Error

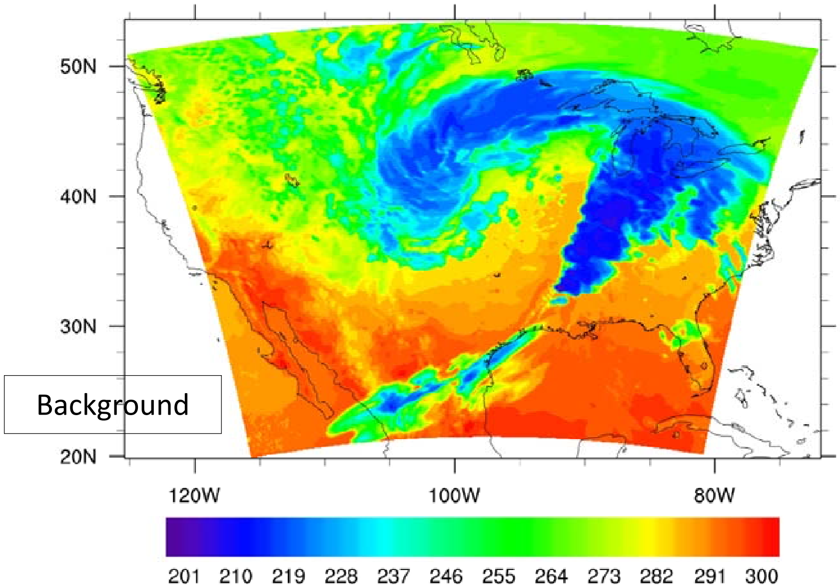


Simulated mismatch in resolution:

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

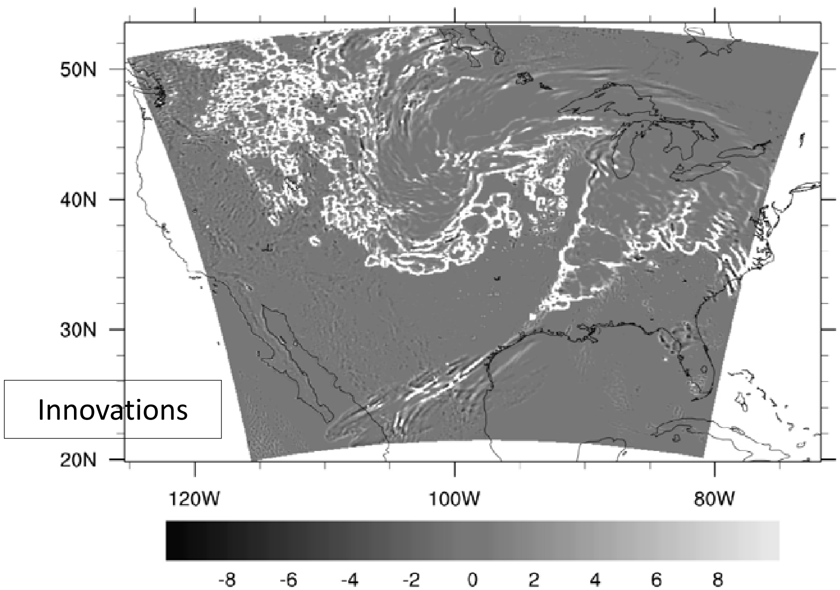


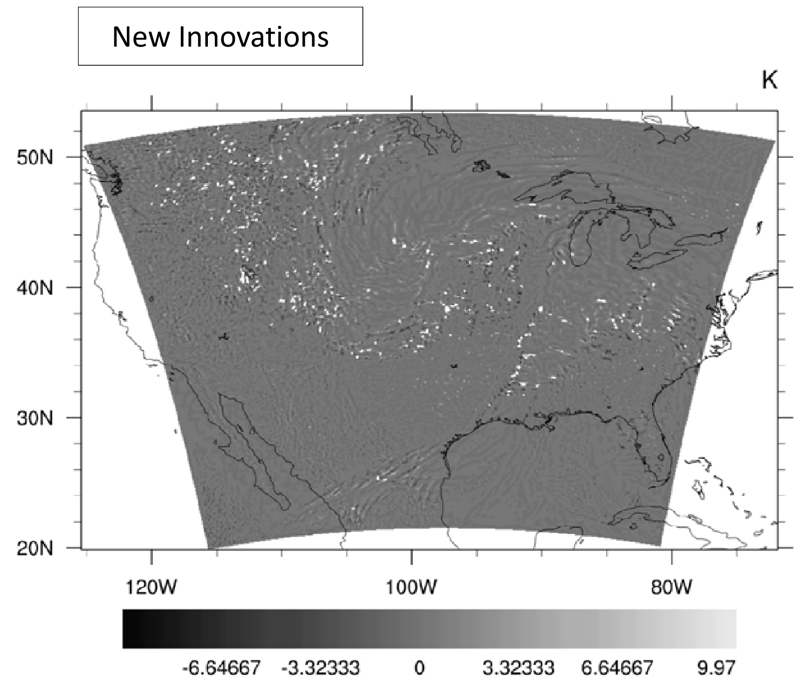
Representativeness Error



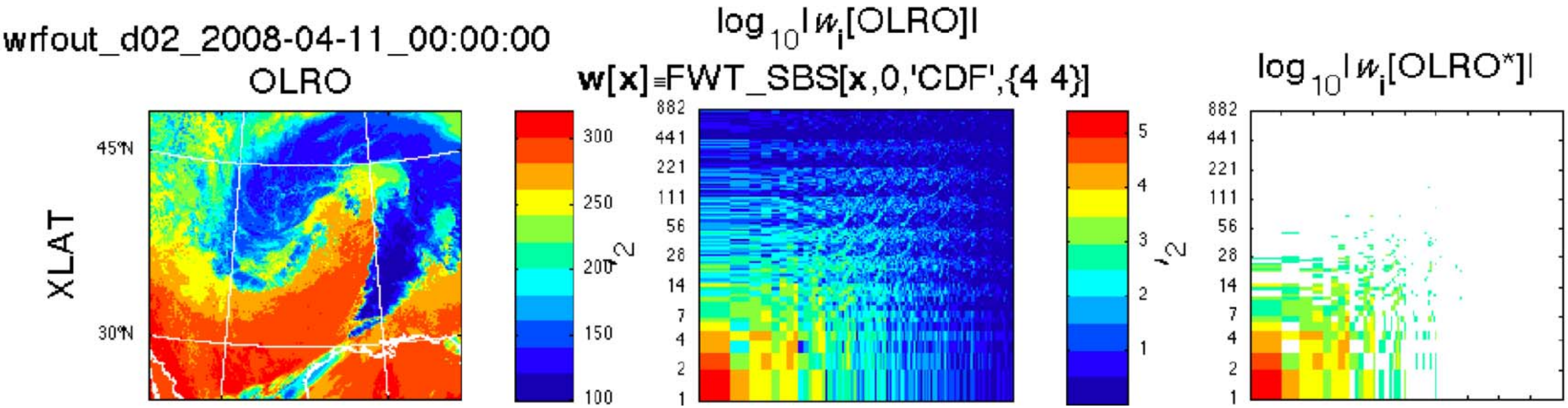
New interpolation scheme:

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





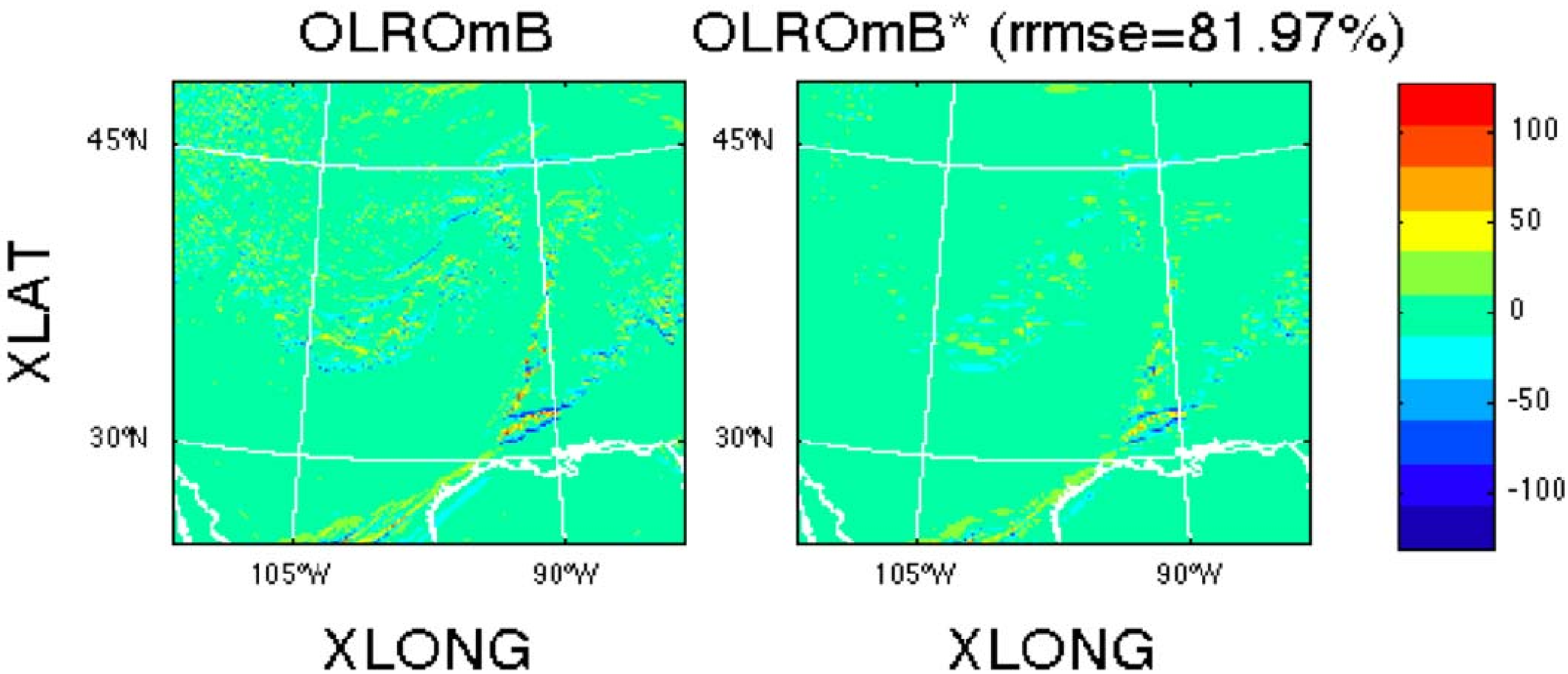
Biorthogonal wavelet transform can *isolate* observation-background differences scale-by-scale while preserving physical-space localization



By sorting and comparing $|w_{\mathbf{i}}|$ for obs. $\mathbf{y}_o$ & background $\mathbf{y}_b$ we can isolate a multi-scale subset $\boldsymbol{i} \in \mathbb{I}$ (right) from which *equivalent* representations $\mathbf{y}_o^*$ and $\mathbf{y}_b^*$ of $\mathbf{y}_o$ and $\mathbf{y}_b$ can be reconstructed…

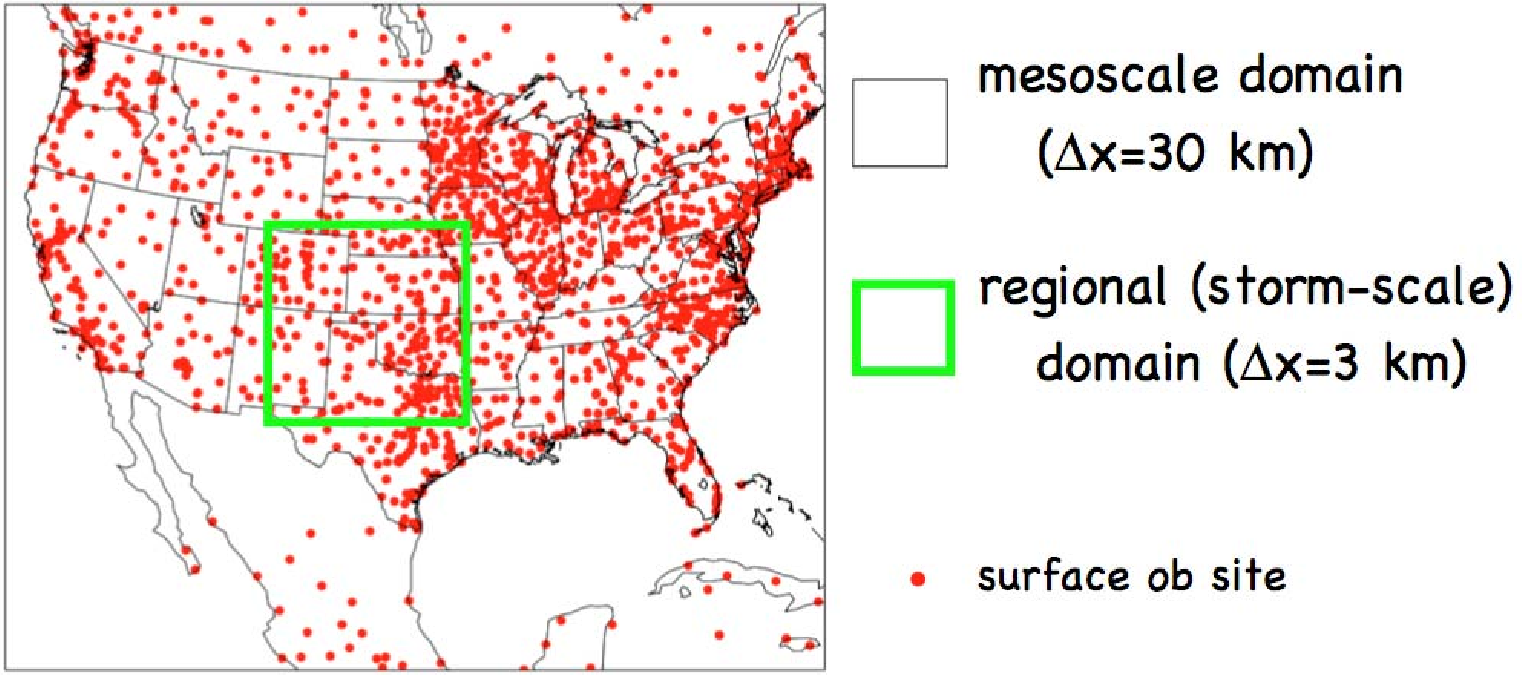
(Aimé Fournier)

Reduction in representativeness error within observation-background differences



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

WRF ensemble

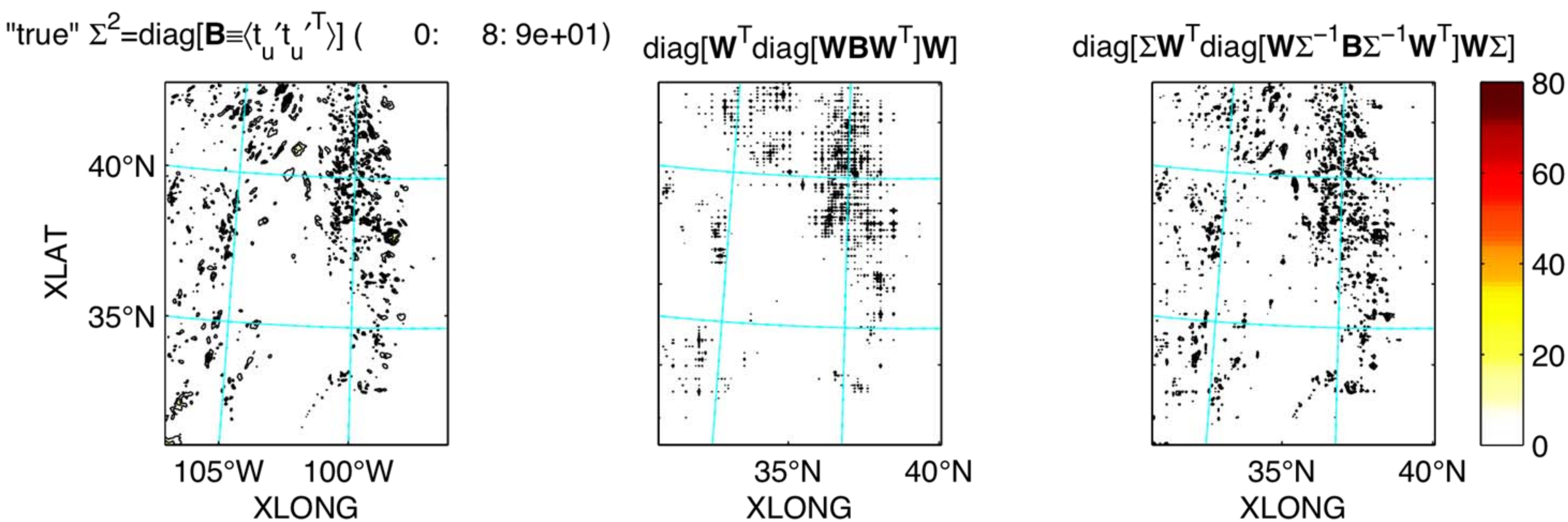


- 30-km ensembles are initialized at 1200 UTC on the day of interest.
  - Multi-physics ensemble
    - PBL (3 schemes), cumulus (3 schemes), shortwave radiation (2 schemes)
  - Ensemble mean and boundary conditions from 1200 UTC NAM
  - Spatial perturbations from an ensemble Kalman filter applied to observations (sounding, surface, aircraft) during the previous 2.5 days
    - Perturbations are mesoscale and flow dependent.
    - Grid-scale dynamics and parameterization diversity increase ensemble spread.
    - Observations decrease ensemble spread.
- Each 30-km ensemble member provides initial and boundary conditions for a 3-km ensemble member.

(David Dowell)

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).



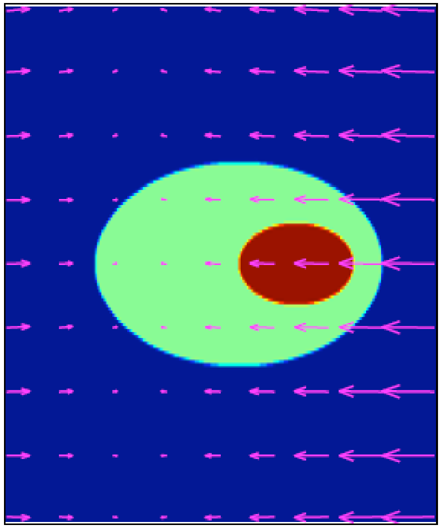
•The normalization with $\mathbf{\Sigma}^2$ = diag **B** (left) yields a model with *fewer* artifacts (right) than does $\mathbf{\Sigma} = \mathbf{I}$ (center) (as found by D&B earlier).

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

(Aimé Fournier)

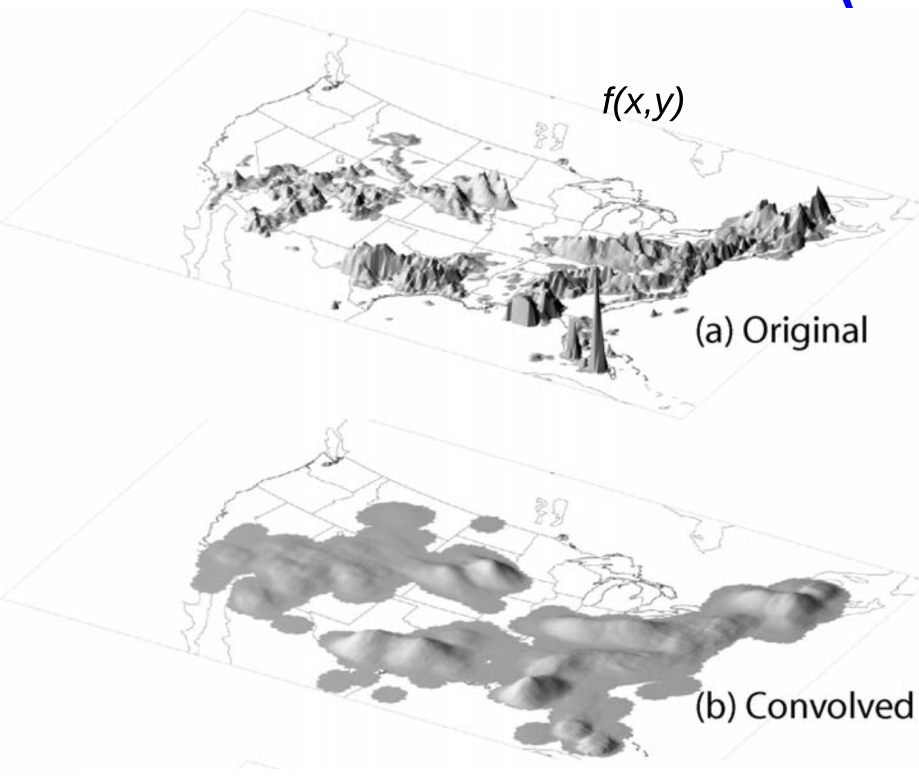
Diagnostic Verification Methods

1. Object-based
2. Field Deformation
3. Neighborhood (fuzzy)
4. Scale Decomposition
5. Variograms

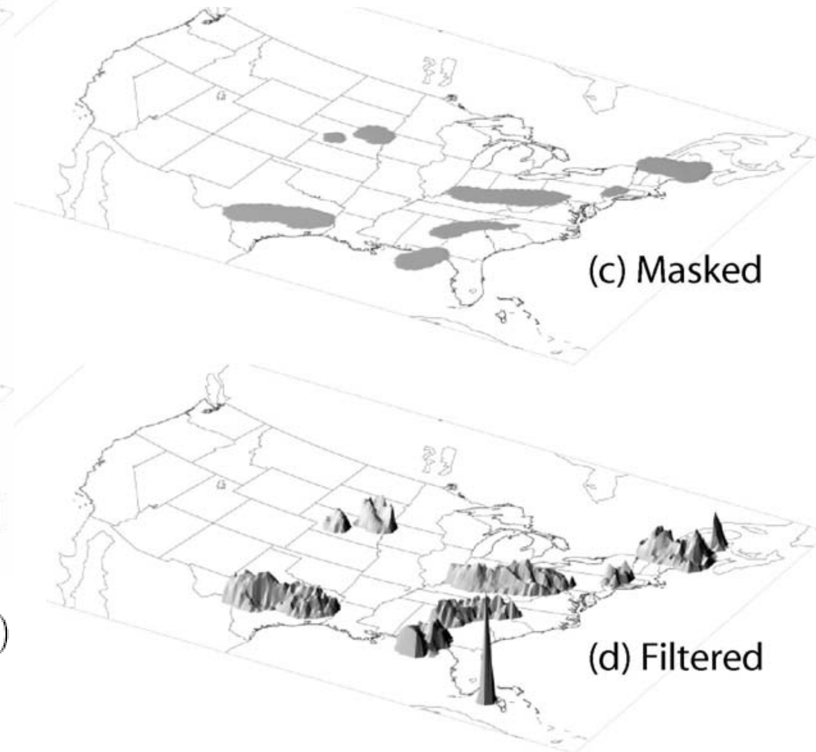


(Chris Davis - http://www.ral.ucar.edu/projects/icp*)*

Method of Object-based Diagnostic Evaluation (MODE)



$$h(x,y) \;=\; \begin{cases} 1 & \text{if } g(x,y) \;\geq\; T \\ 0 & \text{otherwise} \end{cases}$$



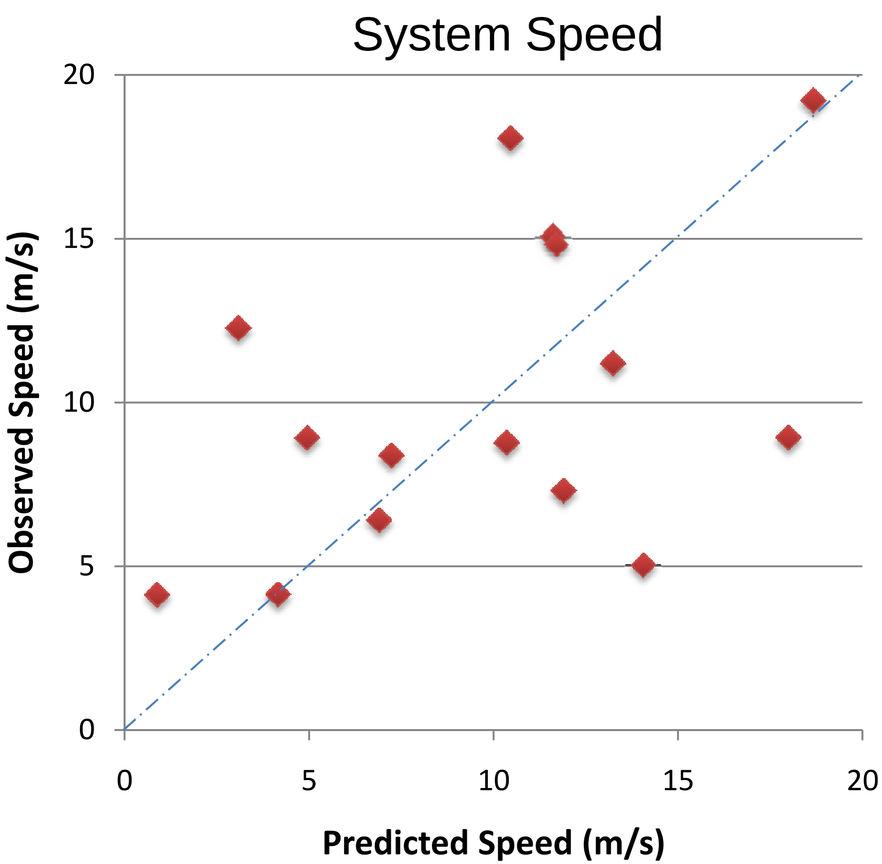
$$g(x,y) \;=\; \sum_{(u,v)\in G} \phi(u,v)\; f(x-u, y-v)$$

$$\phi(x,y) \;=\; \begin{cases} H & \text{if } x^2+y^2 \;\leq\; R^2 \\ 0 & \text{otherwise} \end{cases}$$

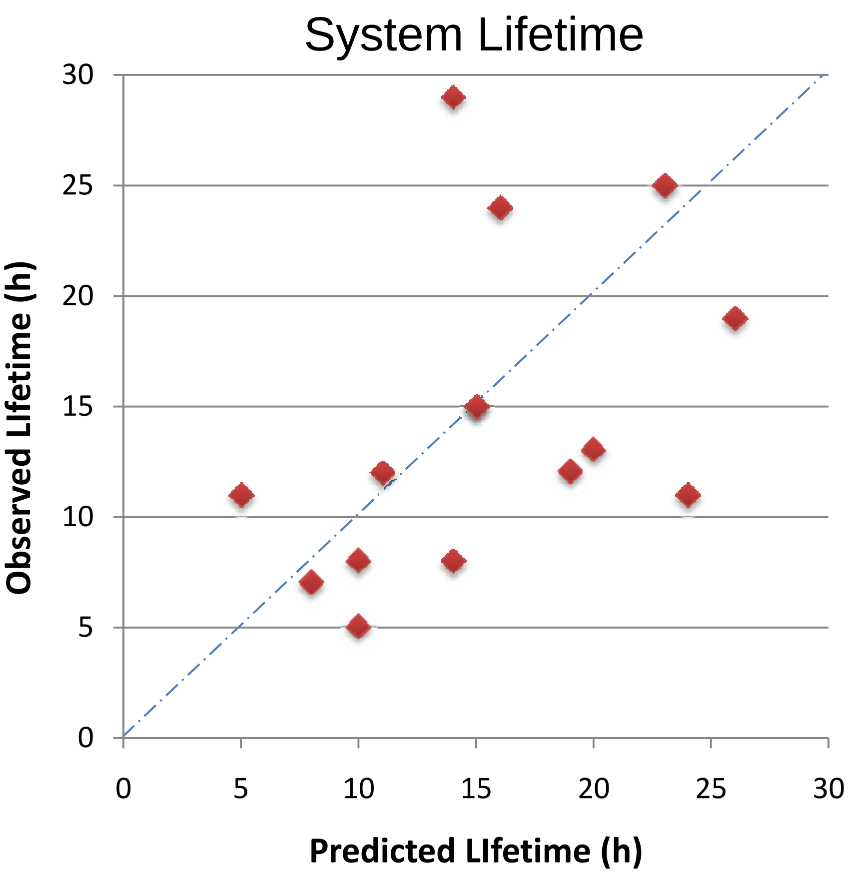
$$\pi R^2 H \;=\; 1.$$

Restore original field where h(x,y) =1

Attributes of Rain Systems



No obvious bias
Limited skill



Small high bias in
predicted lifetime

Status

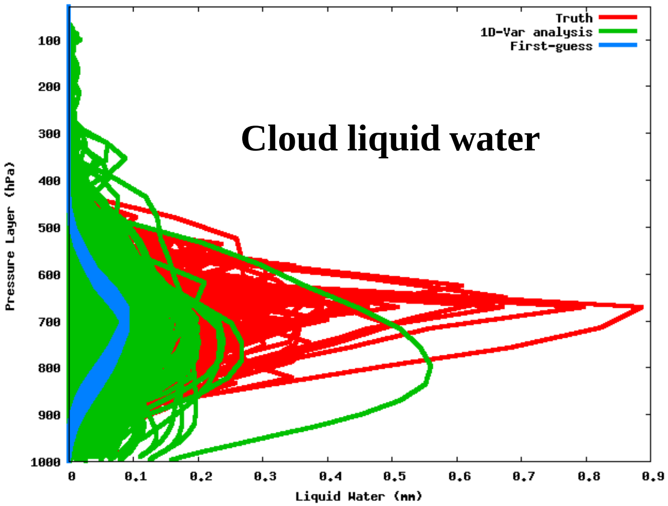
- Think global, start local…
(convective-scale, hurricane DA experiments)
- Research in 4DVar, EnKF, Hybrid
- Simulated & real satellite radiances
- Inhomogeneous Background error modeling
- Verification of cloud forecasts

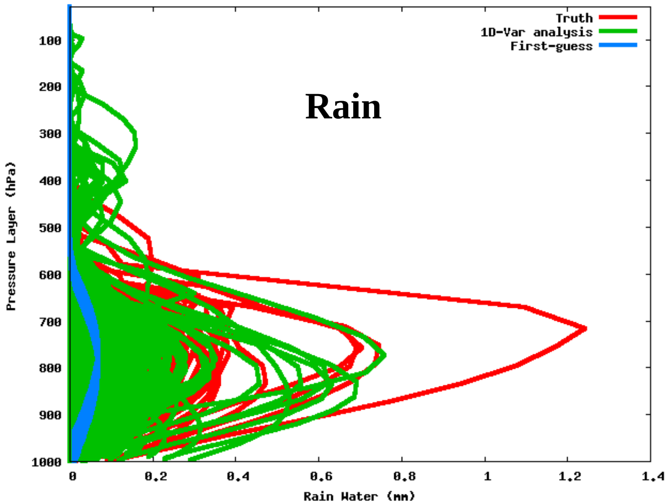
Recommendations

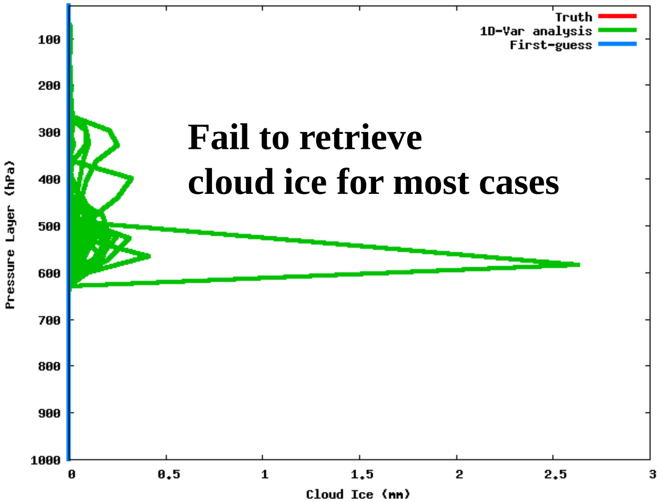
- Will traditional DA methods work for clouds? (*e.g.* non-linear, non-Gaussian)
- Focus on model error (*e.g.* microphysics, RTM)
  - info on model deficiencies
  - new DA techniques
- Leverage Ensemble / Variational experience
- Modular codes
  - increase flexibility
  - facilitate collaborations

Thanks! Questions?

Simulated SSMIS radiances in 1DVAR





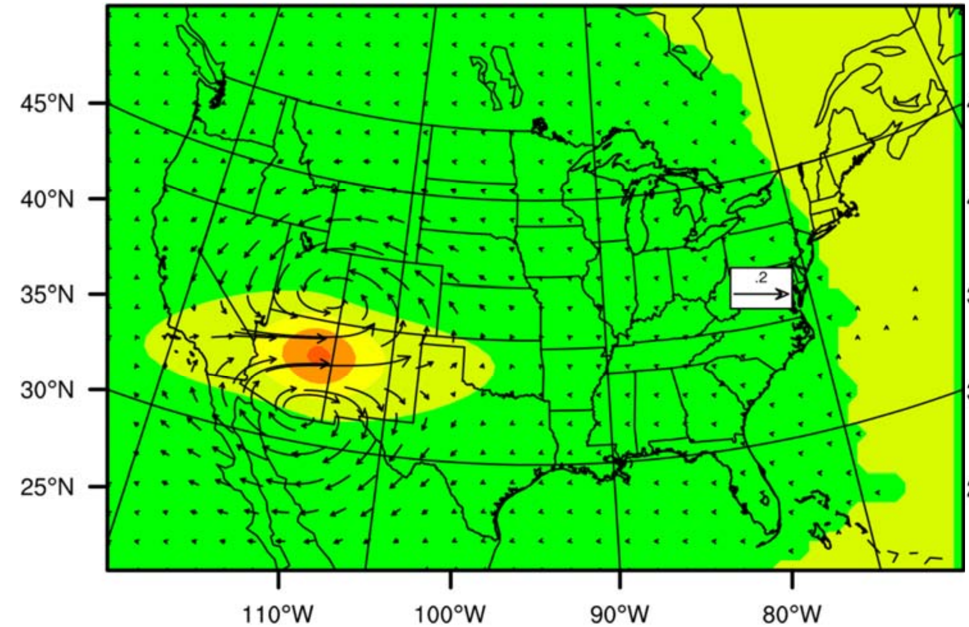


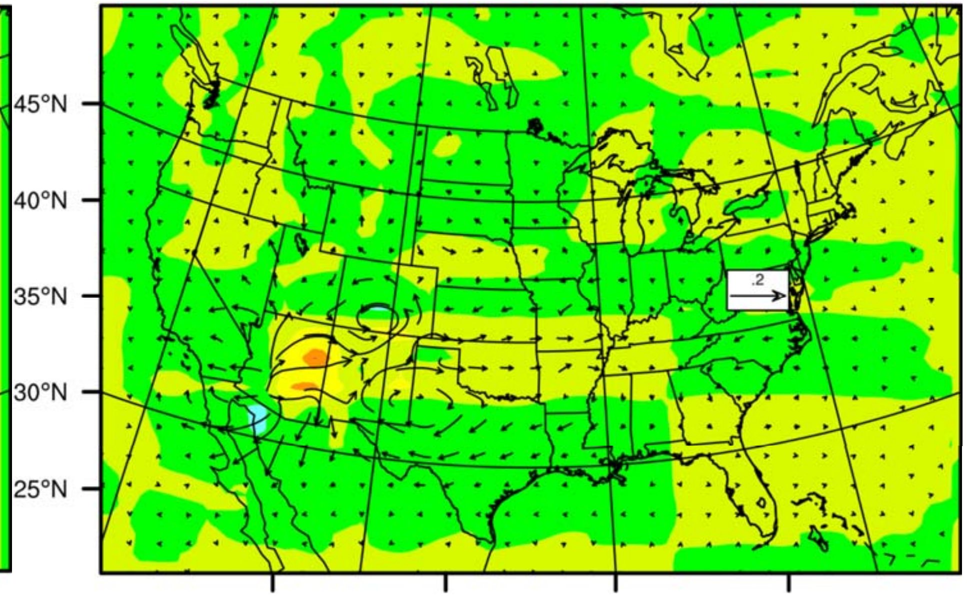
1DVar Retrieval of Hydrometeors

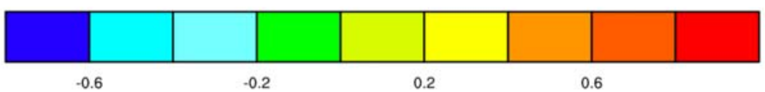
1. Control variables: T, Q, Cloud liquid water, rain, cloud ice
2. Start from a mean cloud/rain profile background
3. Random noise to the simulated obs and T, Q background profiles

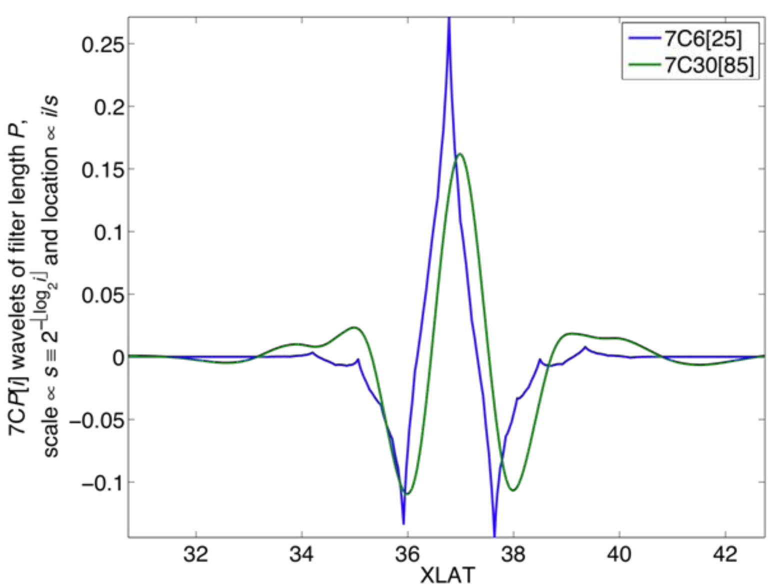
Signal for cloud-ice is weaker than for cloud-water/rain

Need a better preconditioning?





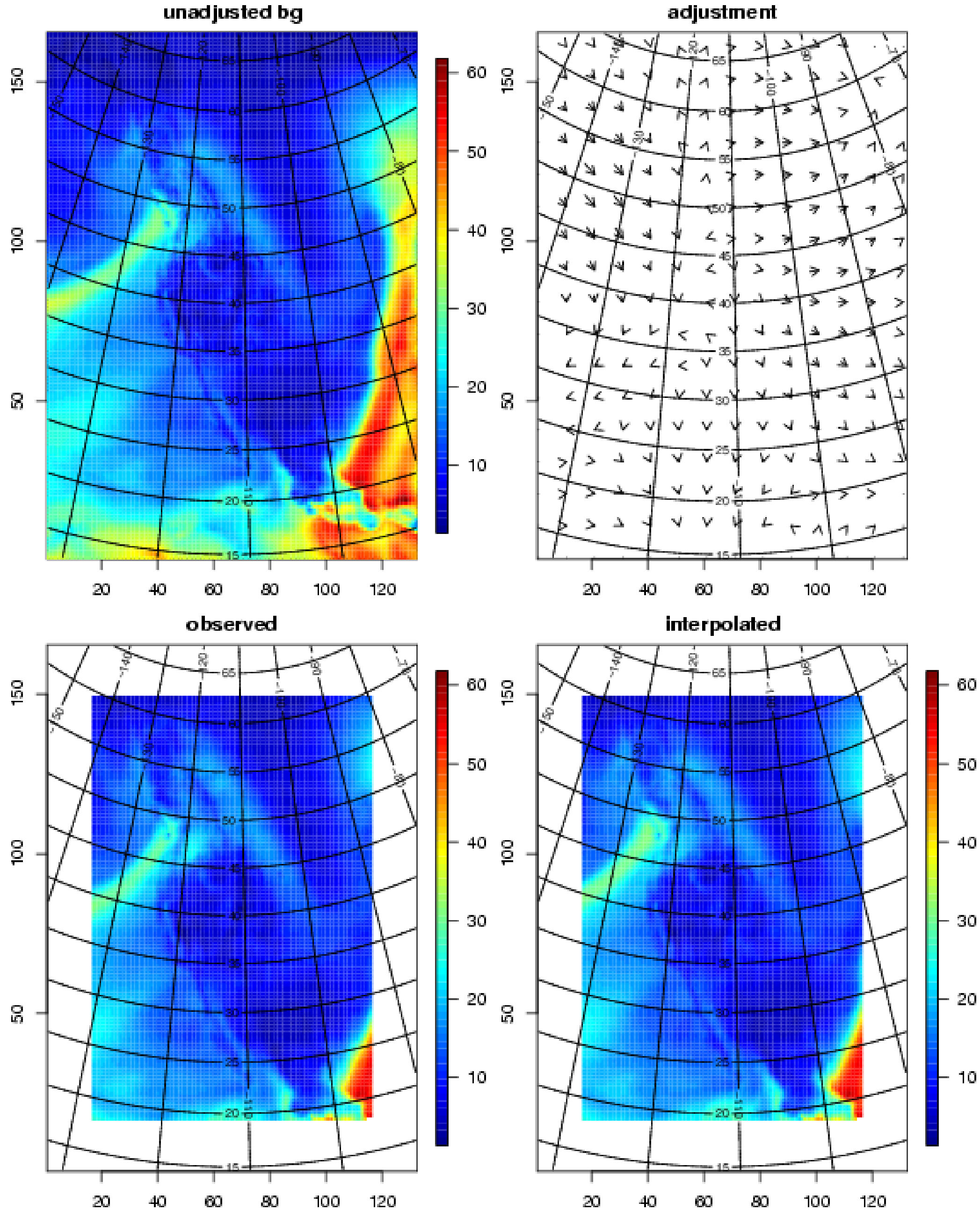




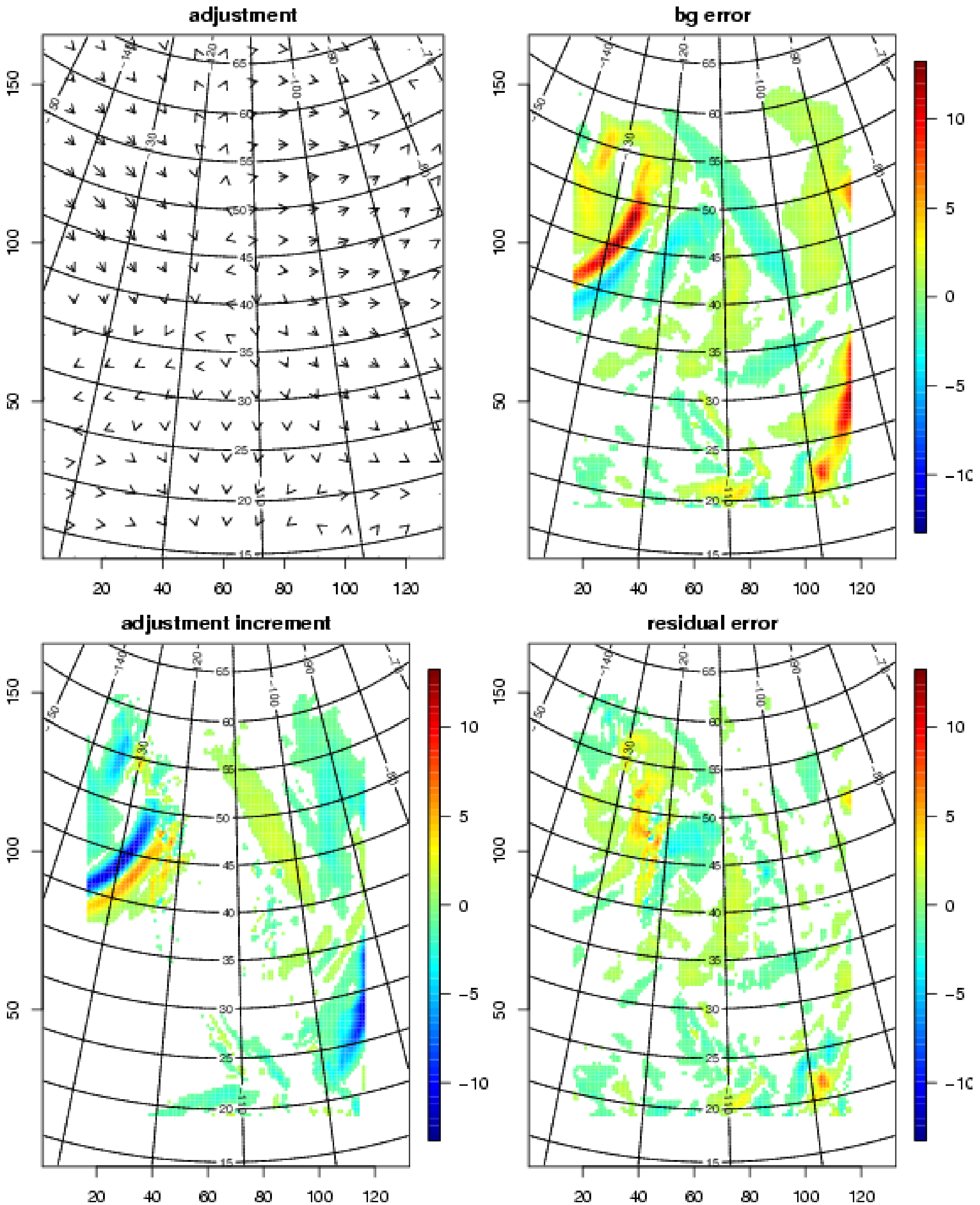
The wavelet B model (right) represents *heterogeneity*, unlike homogeneous recursive filters (left)

The filter length can be chosen appropriately for the field smoothness *e.g.*, velocity being smoother than humidity

Displacement data assimilation



Displacement data assimilation



Displacement data assimilation