

Correcting for Position Errors in Variational Data Assimilation

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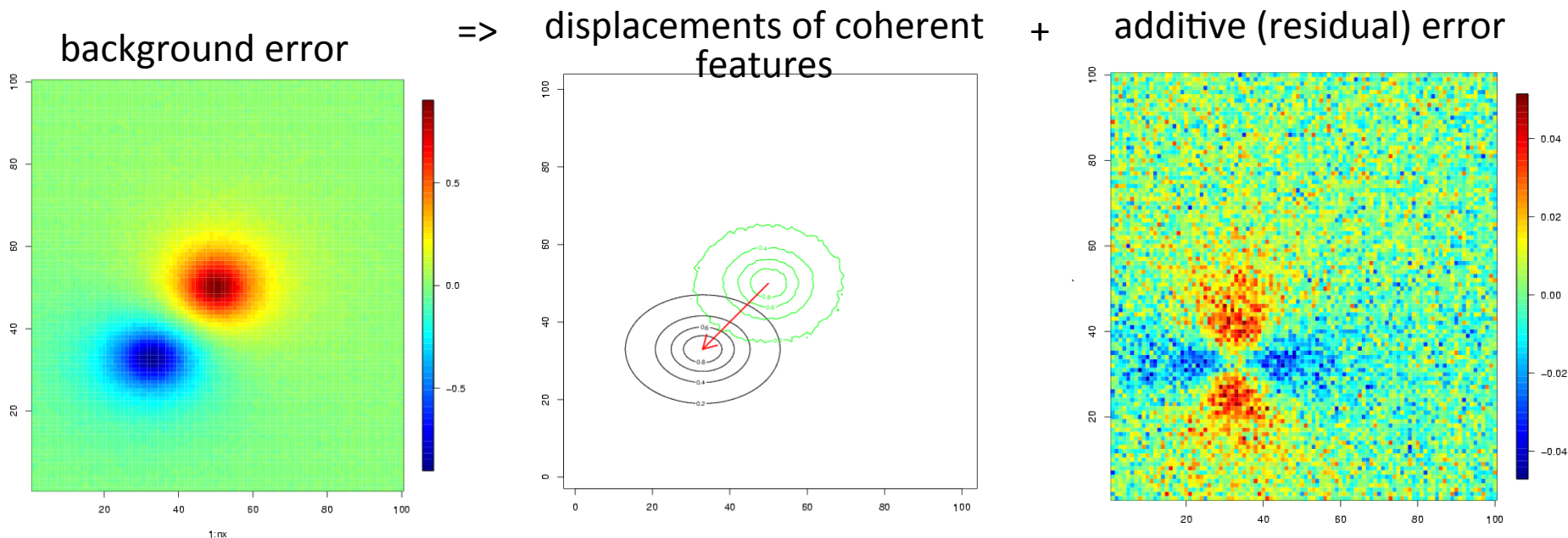
JCSDA Seminar
Monday, November 10, 2014

Outline

- Feature Calibration and Alignment (FCA):
 - Formulation as a stand-alone procedure
 - Katrina example
 - Other examples: characterization of ensemble spread
 - *2014 MWR article: 142, 2, 686-702*
- Displacements within variational DA
 - Displacement WRFDA (dWRF) formulation
 - Katrina example
 - *MWR article currently under review*
 - Other examples: GOES IR channels
- Conclusions, future work

Feature Calibration and Alignment (FCA)

- For cloud-related fields, position errors of features are both common and problematic
 - Non-Gaussian error statistics
 - Poor convergence of variational analysis schemes
- FCA represents errors (or differences) in terms of errors of alignment and errors of amplitude and “random” errors
 - Here we do not consider FCA amplitude errors



FCA Formulation

- Based on feature calibration and alignment implementation by Grassotti et al. (1999)
- Derive 2D displacement vectors $\mathbf{s}$ by nonlinear minimization of an objective function:

$$J = J_{res} (y^{obs}, y^{bg}, \mathbf{s}) + J_{pen} (\mathbf{s})$$

- Residual errors after adjustment of the background:

$$J_{res} = \sum w_{obs} (y^{obs}(\mathbf{r}) - y^{bg}(\mathbf{r} - \mathbf{s}))^2$$

FCA Formulation

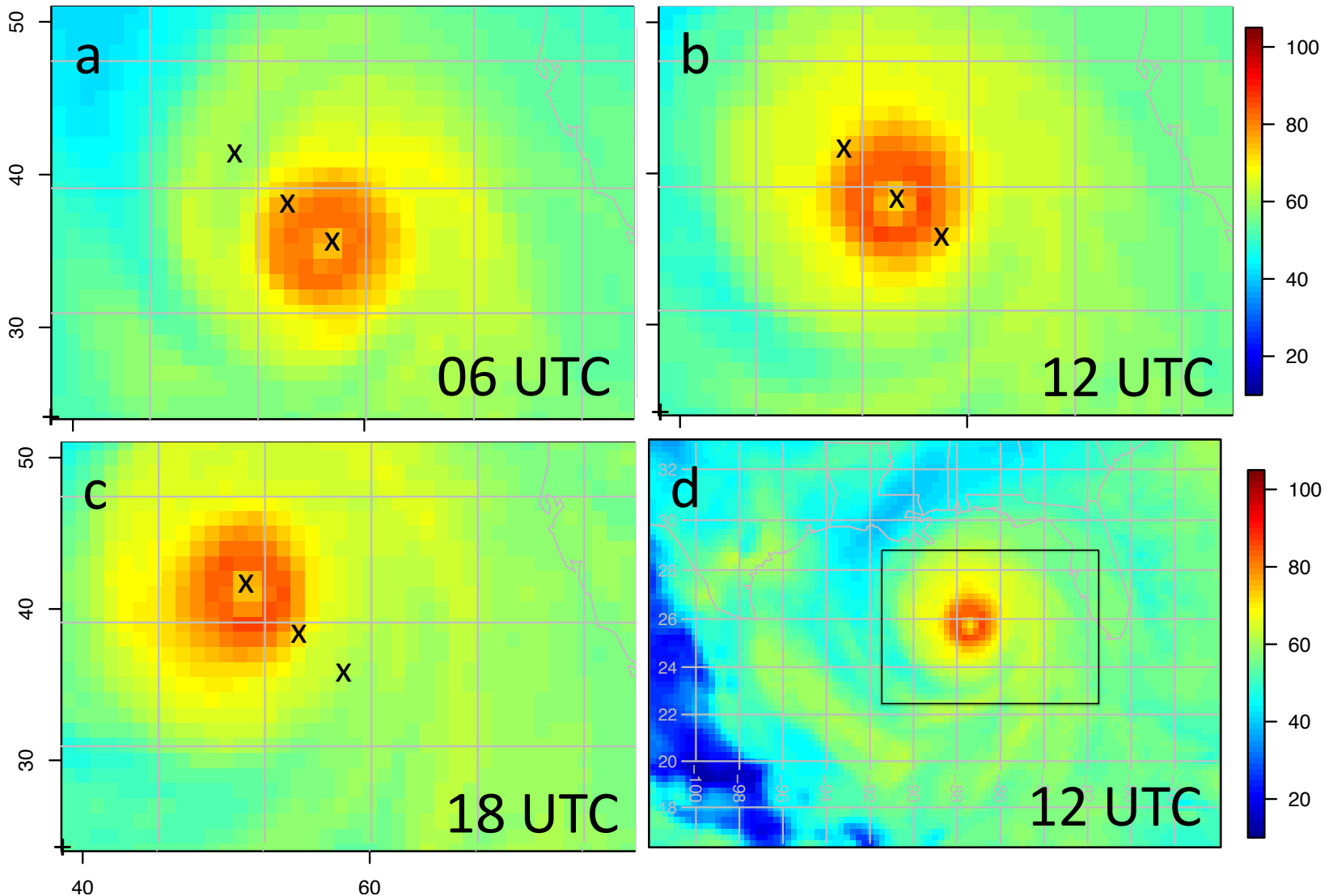
- Use a truncated spectral representation of displacements
- Regularization using tunable constraints (penalty functions):

Constraint	Formula	Gridpoint / Spectral
Smoothness	$\sum S_x^{-2} (\nabla^2 \mathbf{s})^2$	Spectral
Magnitude	$\sum S_x^{-2} \mathbf{s} ^2$	Spectral
Barrier	$\sum (\mathbf{s} / S_x)^{20}$	Gridpoint
Divergence	$\sum (\nabla \mathbf{s})^2$	Gridpoint

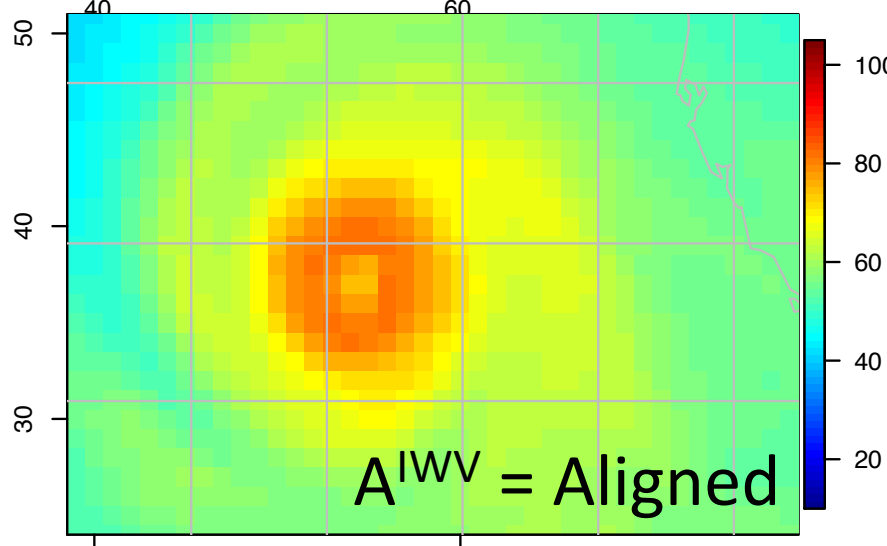
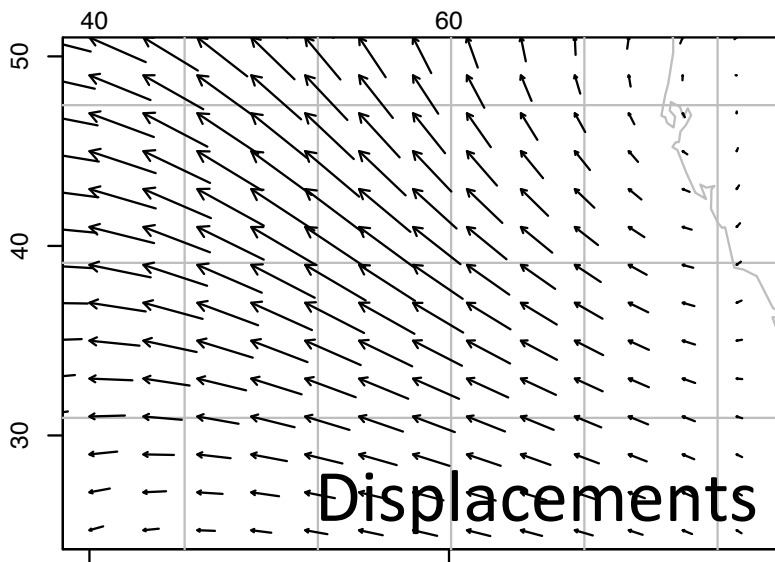
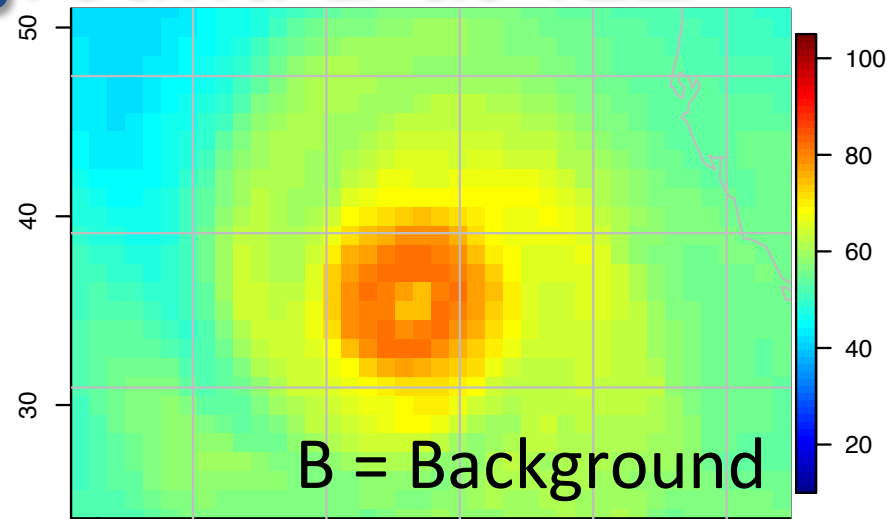
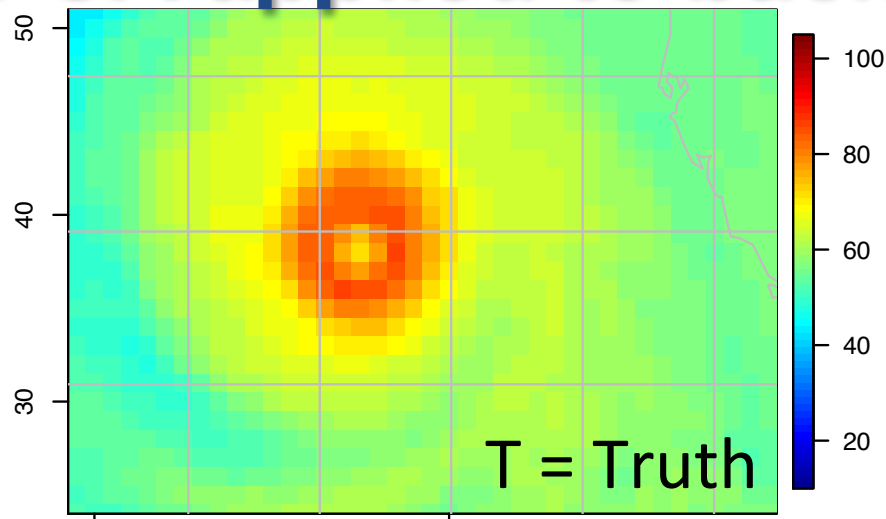
Katrina example

- Adjusting forecast IC in a perfect model case
 - Nature (Truth): control forecast at 12 UTC
 - Background (First guess): control forecast at 06 UTC
 - 2d fields: integrated water vapor (IWV) from Truth, subsampled (every 3rd grid point)

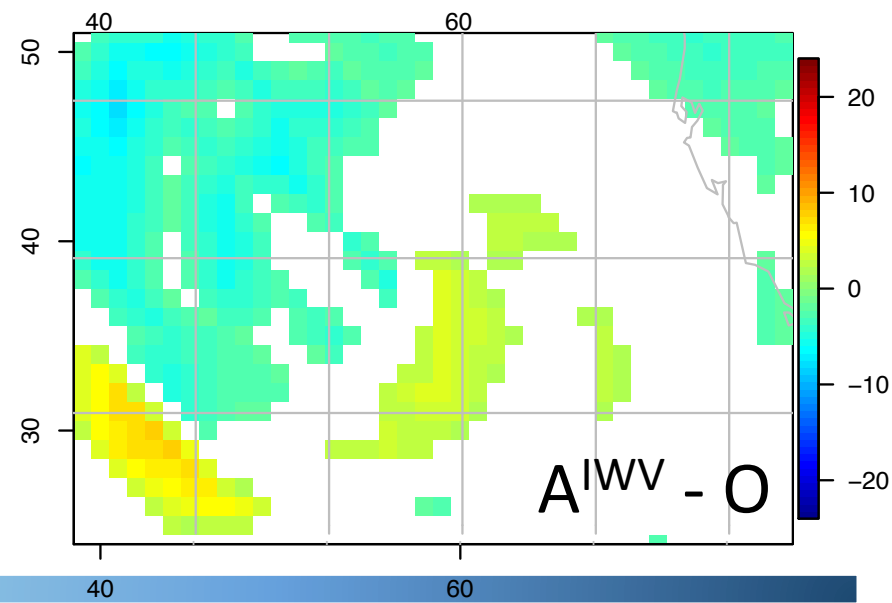
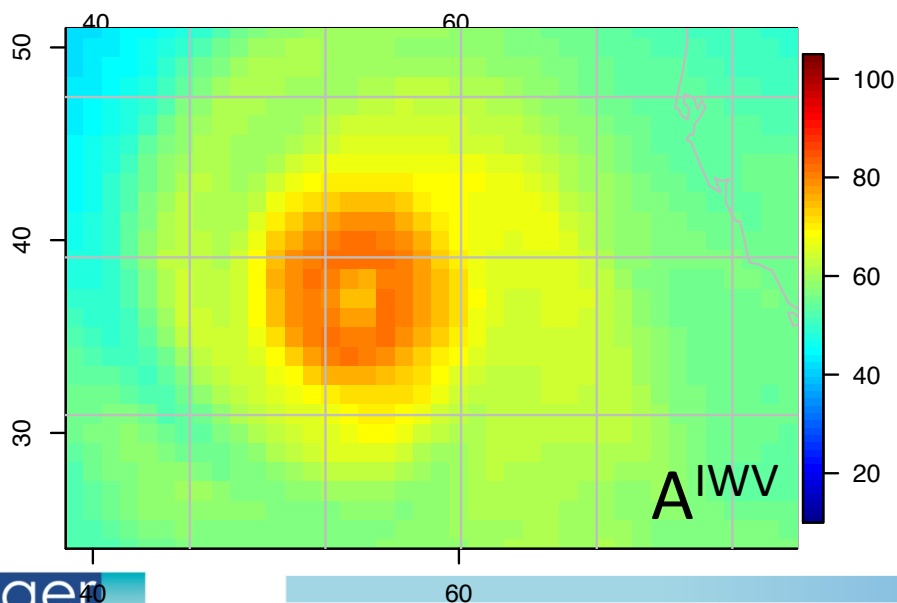
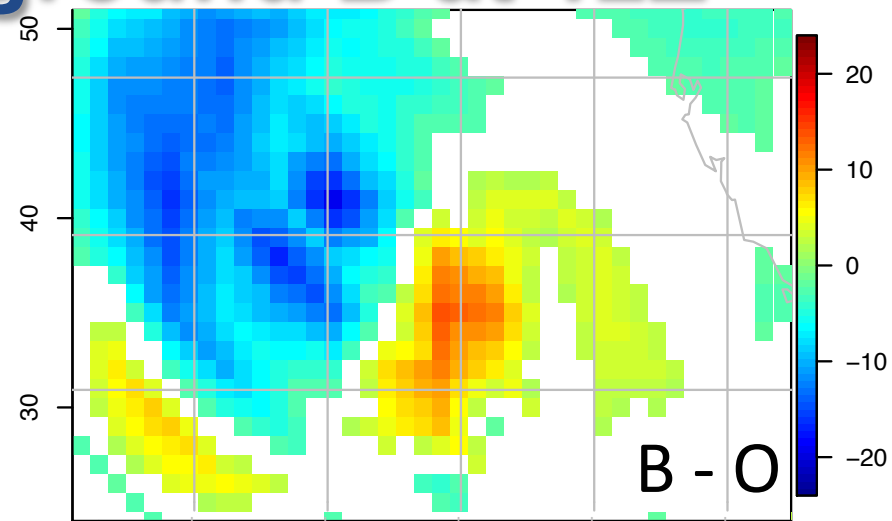
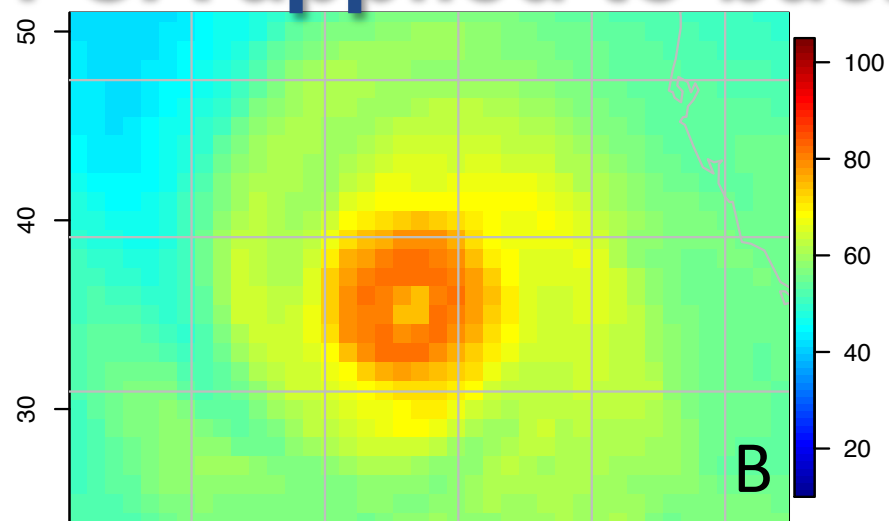
Katrina simulation IWV (kg/m^2) 28 Aug 2005



FCA applied to background B at 12Z



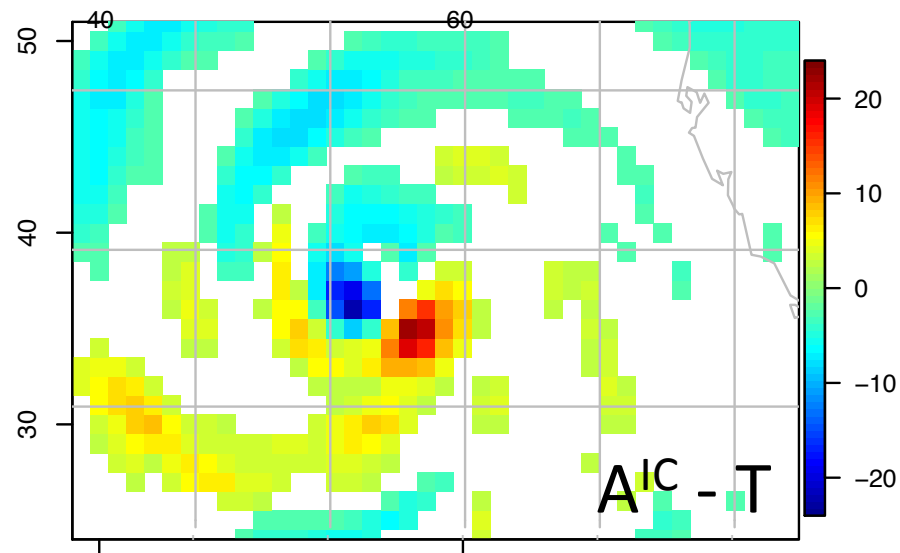
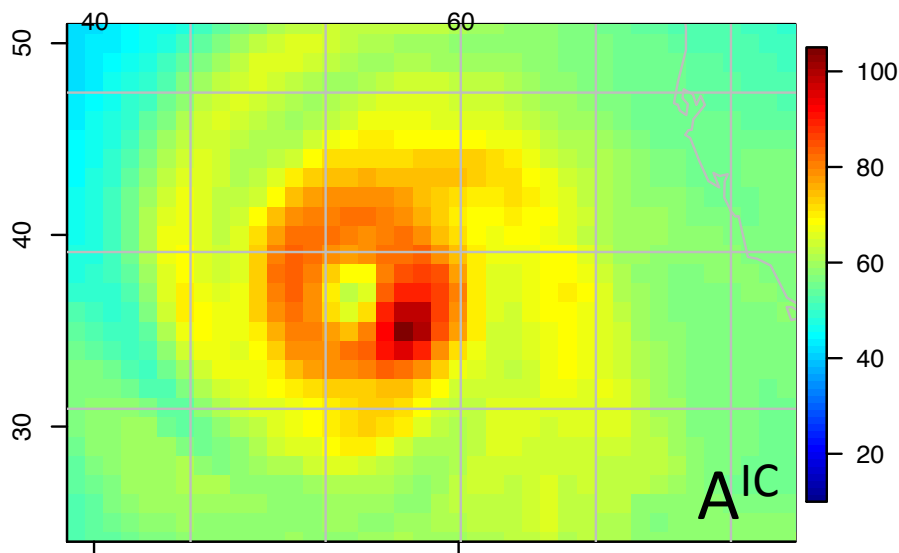
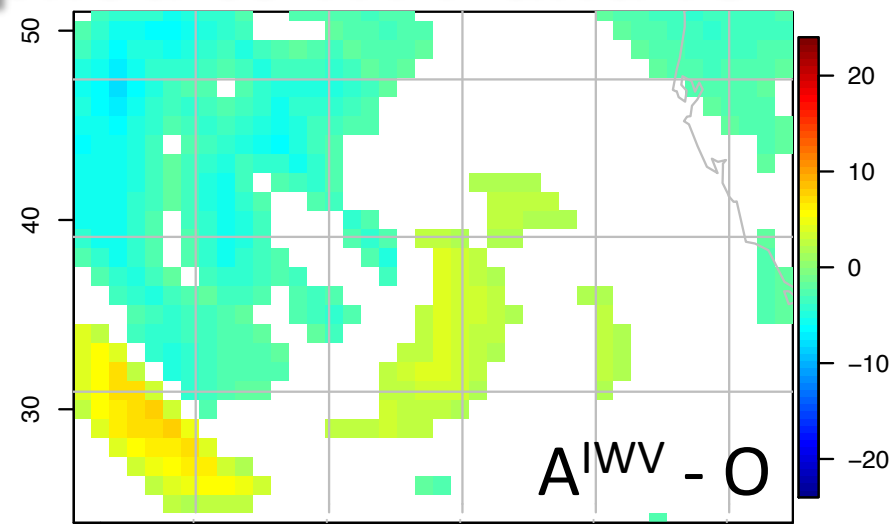
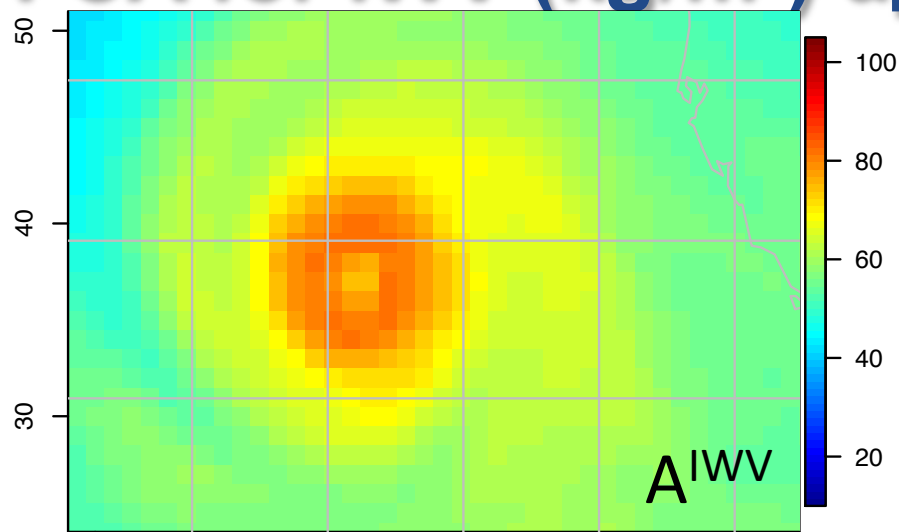
FCA applied to background B at 12Z



Extend Hsiao et al. (2010) displacement algorithm for 3d model IC

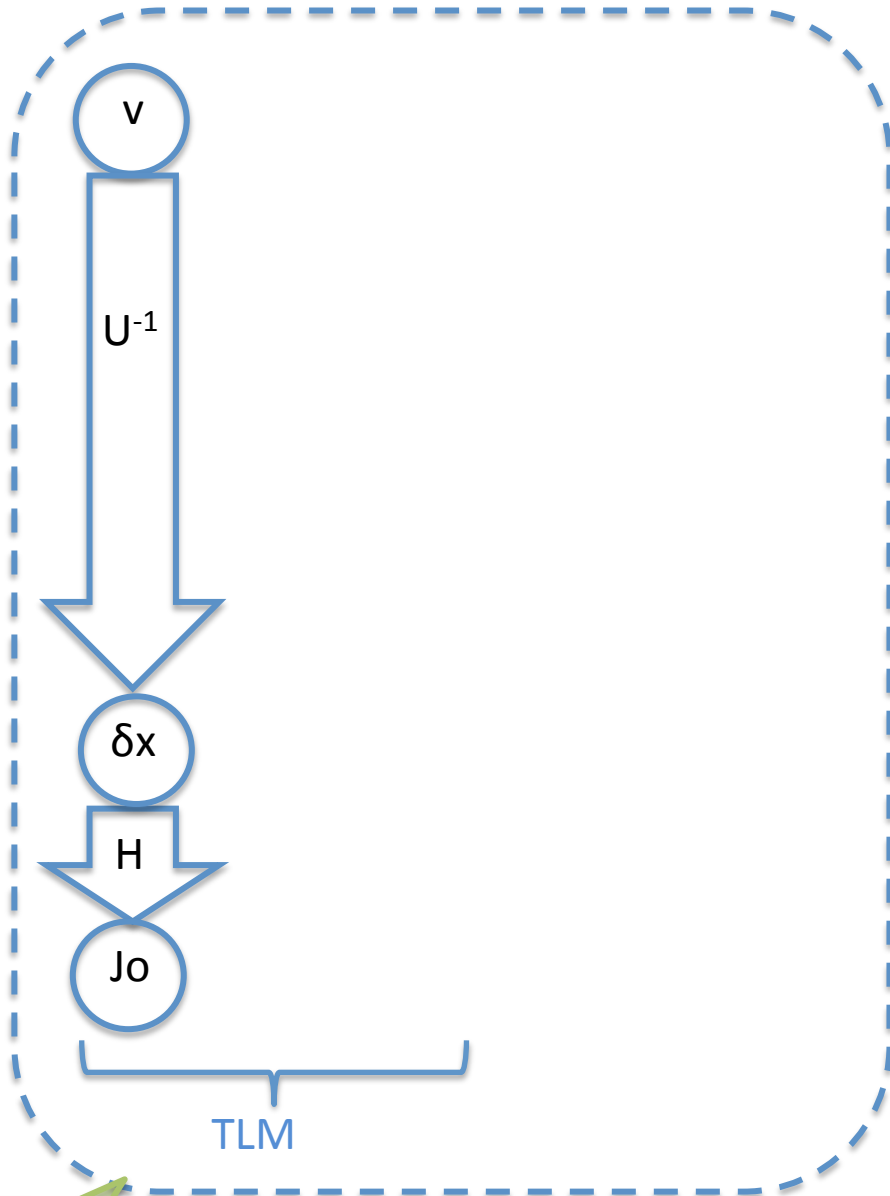
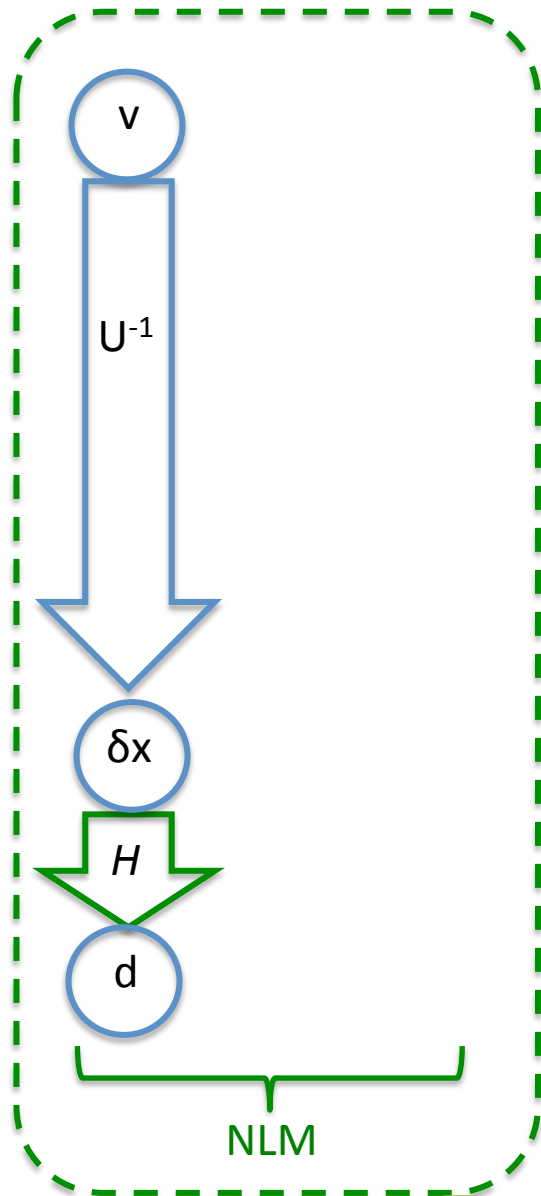
- Goal is to apply 2d displacement vectors to 3d model fields without disturbing model balance
- Direct displacement of: winds (u,v,w), SLP, RH, hydrometeor mixing ratios, potential temperature
 - All along model surface, except
 - Potential temperature along constant height surfaces
- Recalculate derived quantities: pressure, specific humidity, temperature, hydrostatic geopotential, dry air mass
- Nonhydrostatic geopotential is not displaced

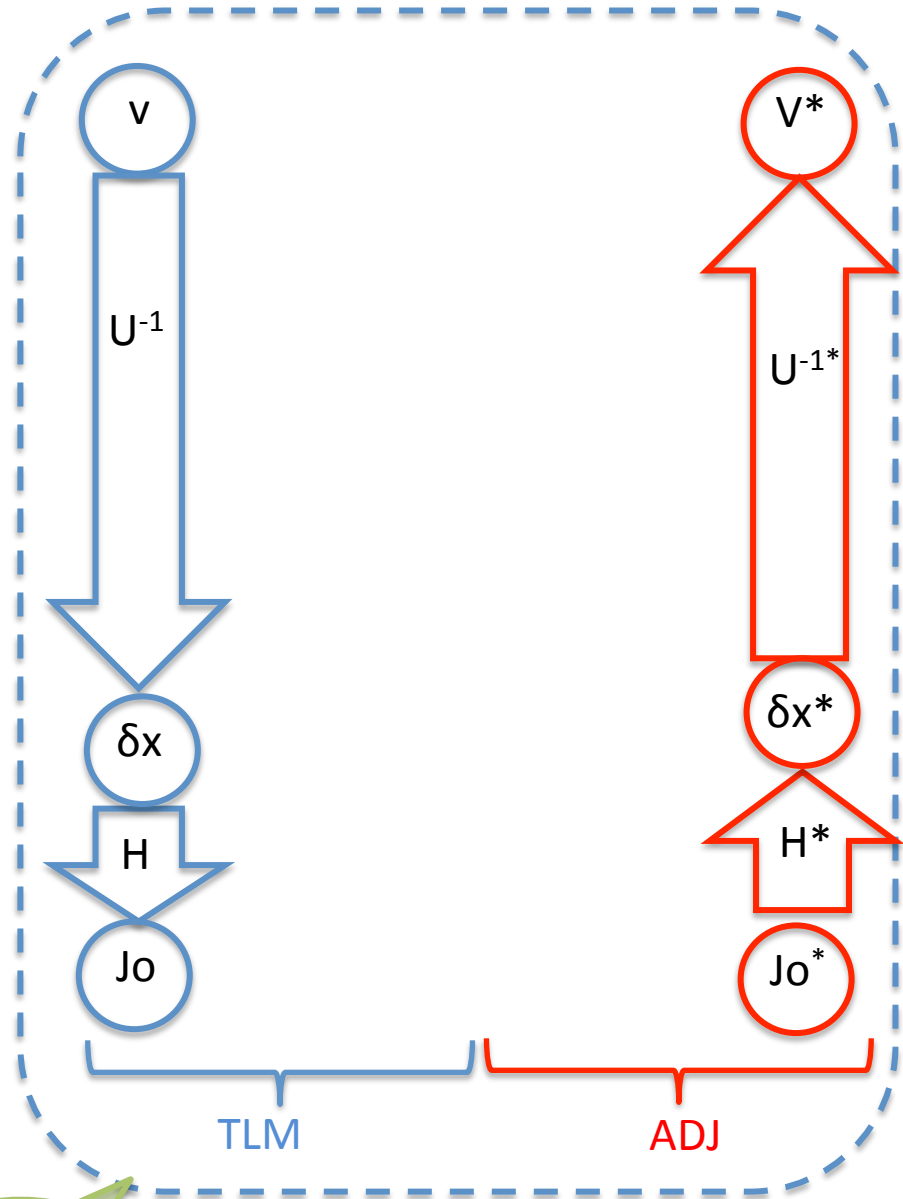
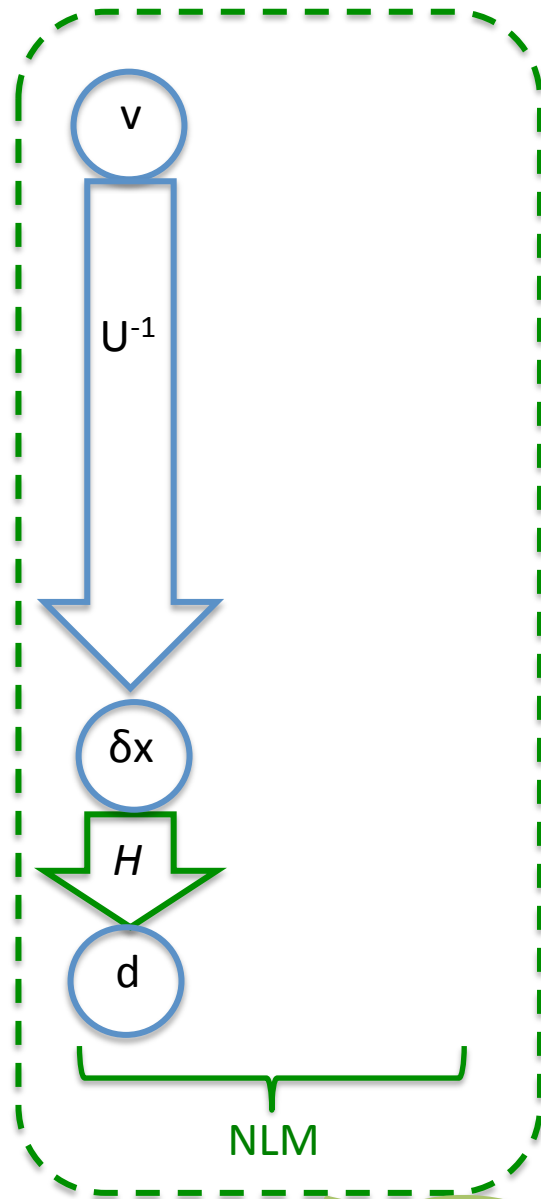
FCA for IWV (kg/m^2) applied to IWV and IC

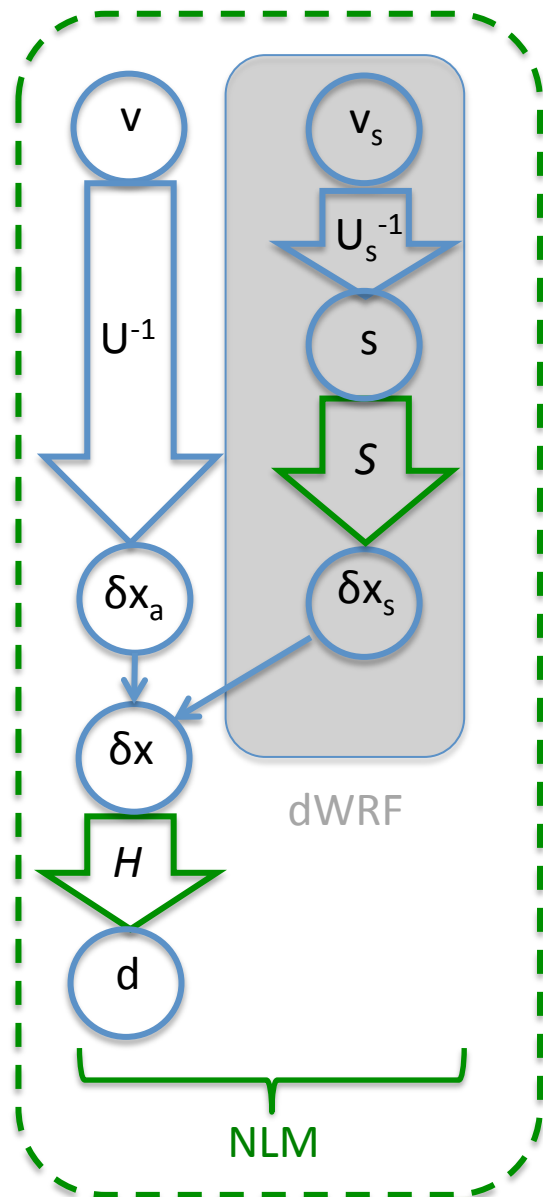


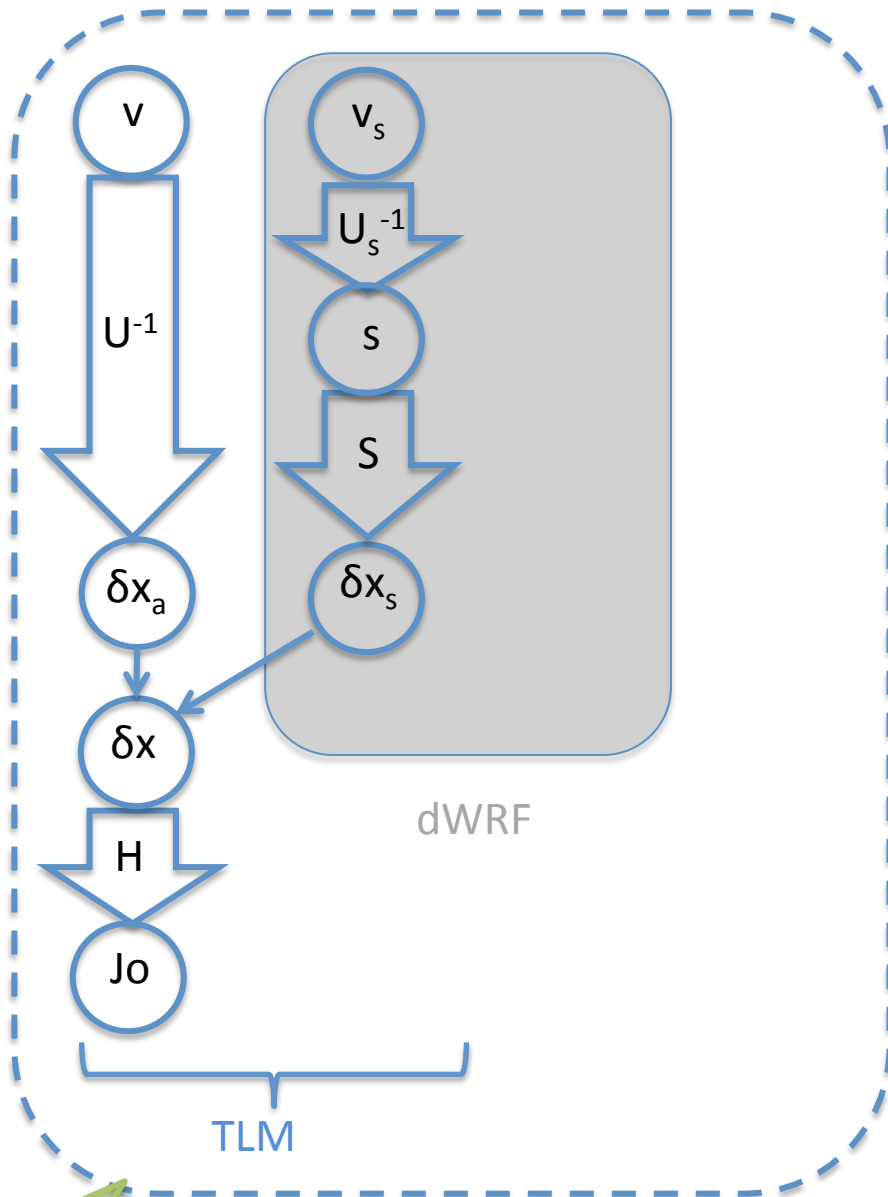
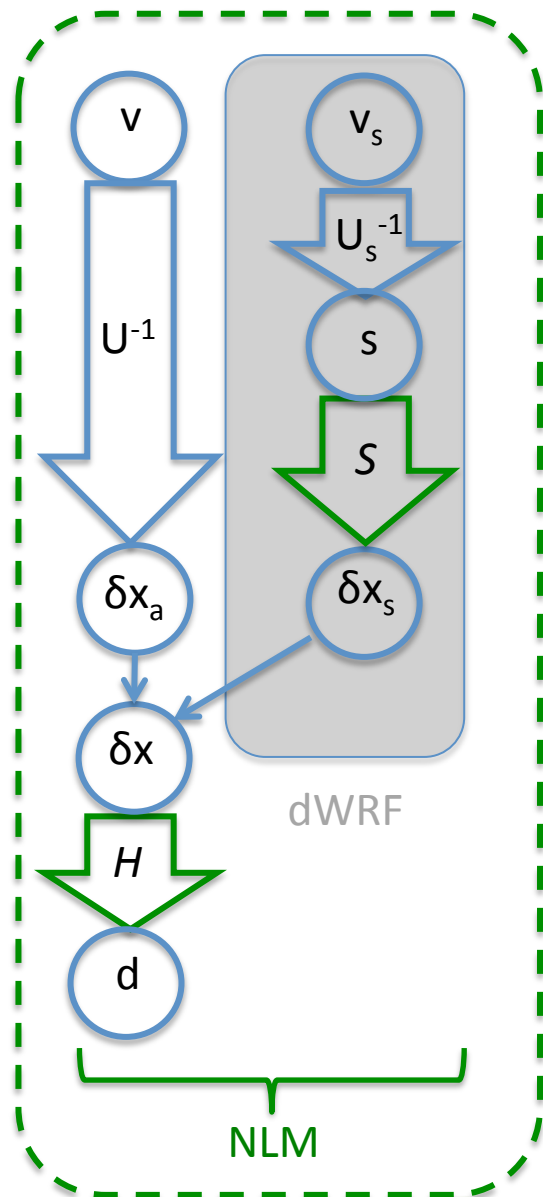
dWRF: Displacements added to WRFDA control vector

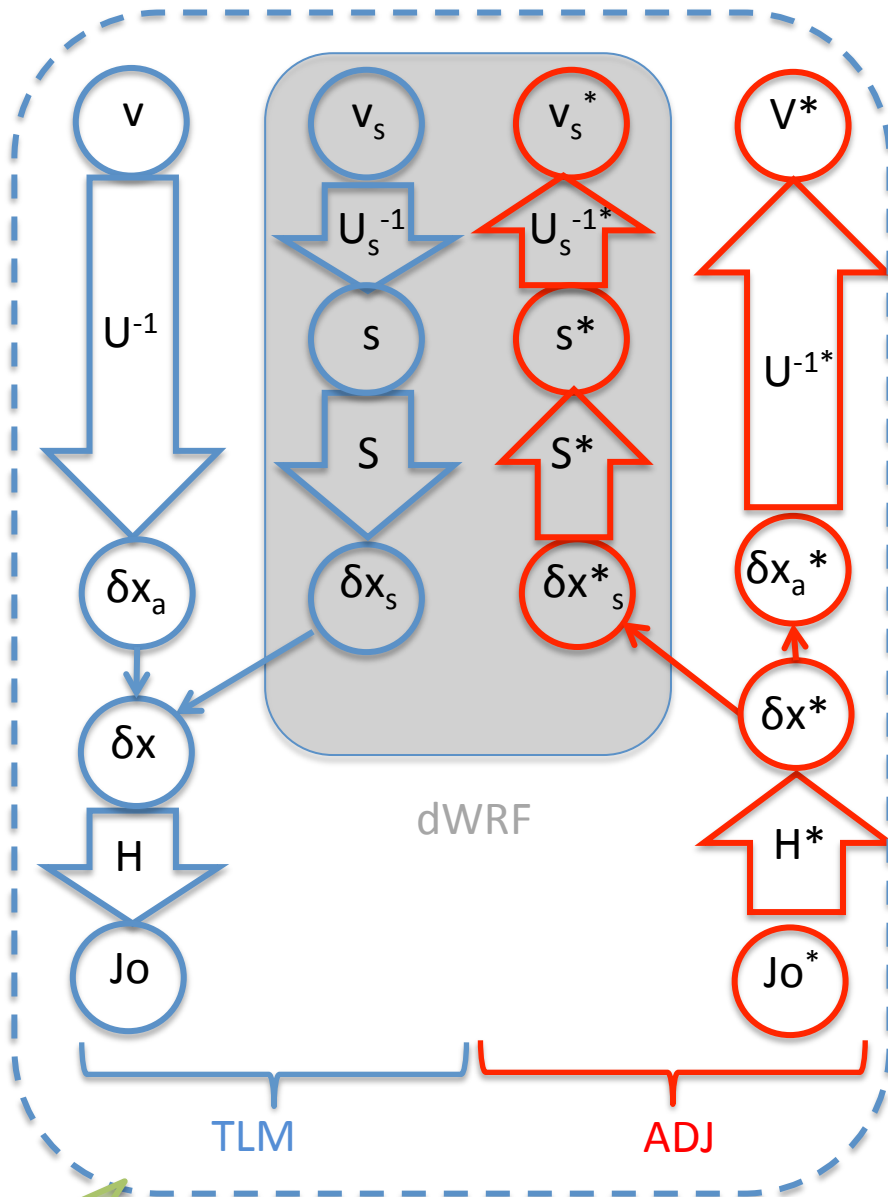
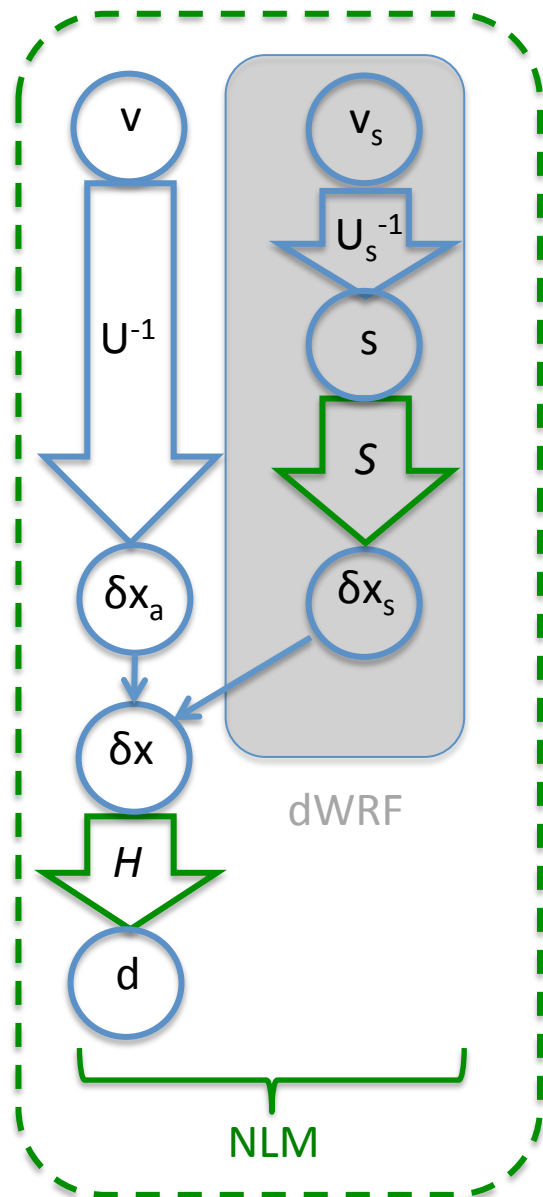
- Hijack u and v for displacements
 - Background function measures size of displacements
 - Examples shown use simple rescaling of error covariances for winds
- Apply displacement to 3-d model fields
 - Parallel implementation, inner loop linearized about current estimate of the displacements
- Otherwise standard 3dvar
 - Usual control variable, but only mid-level u, v are active
 - Existing minimization
 - Conjugate gradient in inner loop with linearized displacements; nonlinear adjustments in outer loop
 - Existing obs operators
 - Therefore this approach is applicable to all obs types supported by WRF Variational DA
 - Following example uses simulated GPS PW

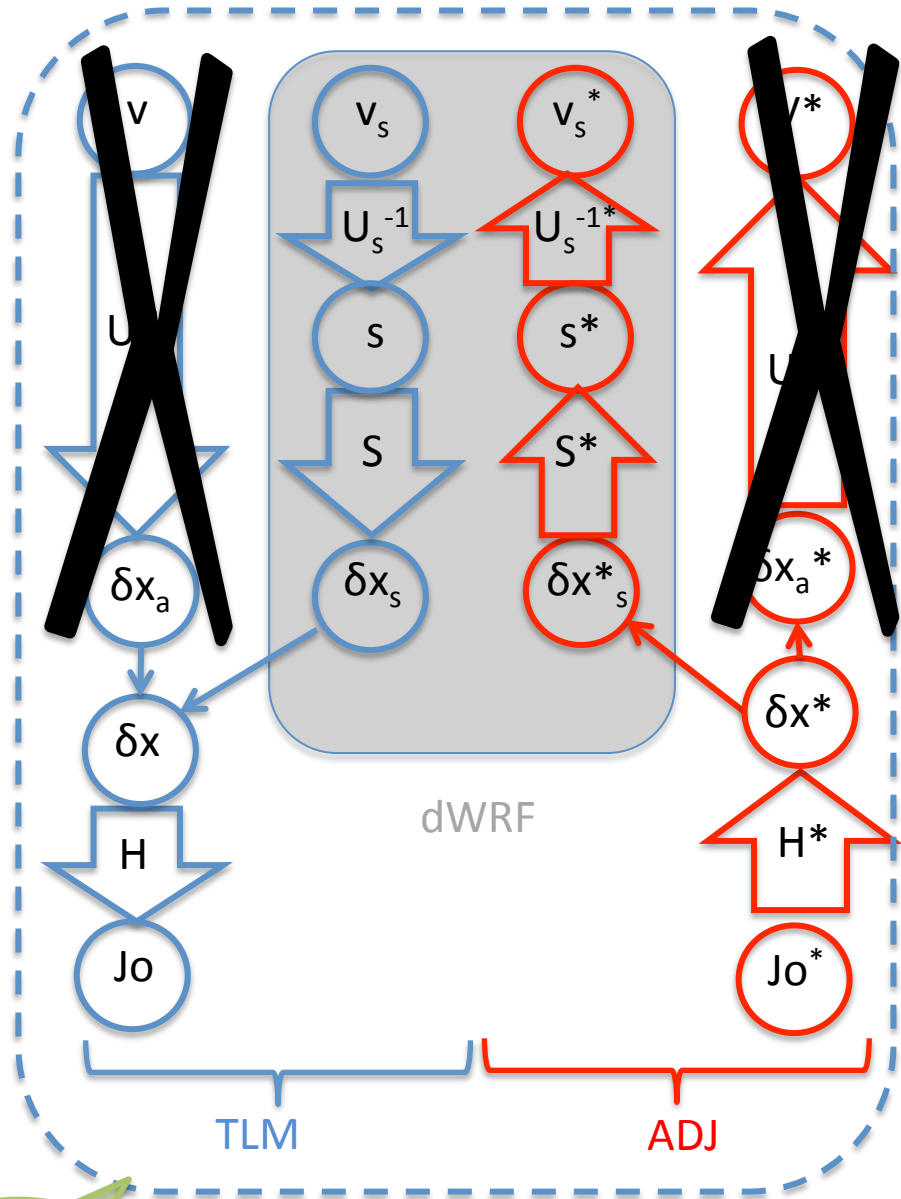
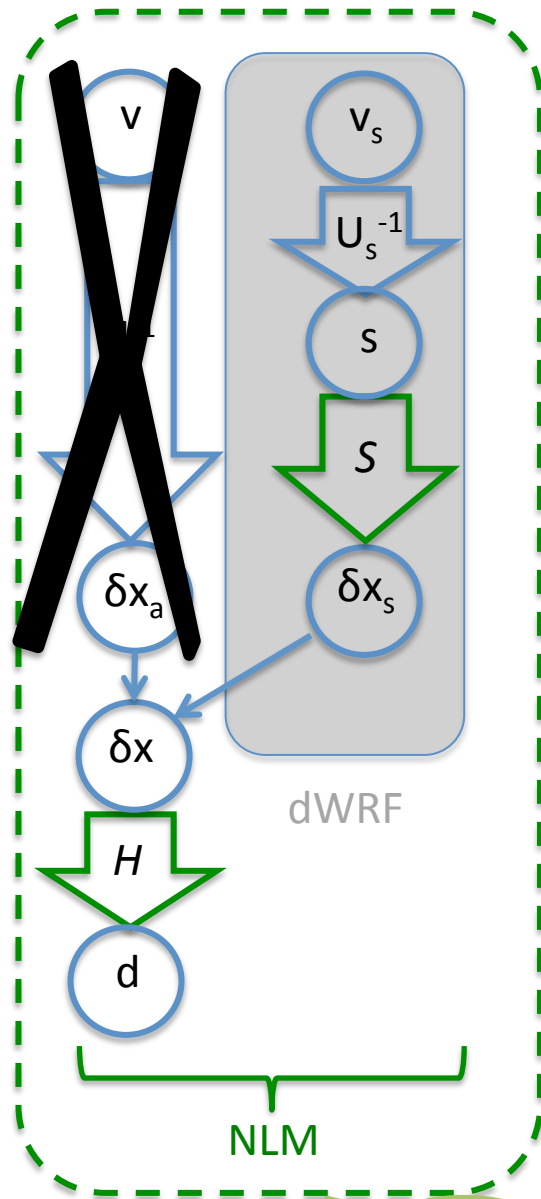




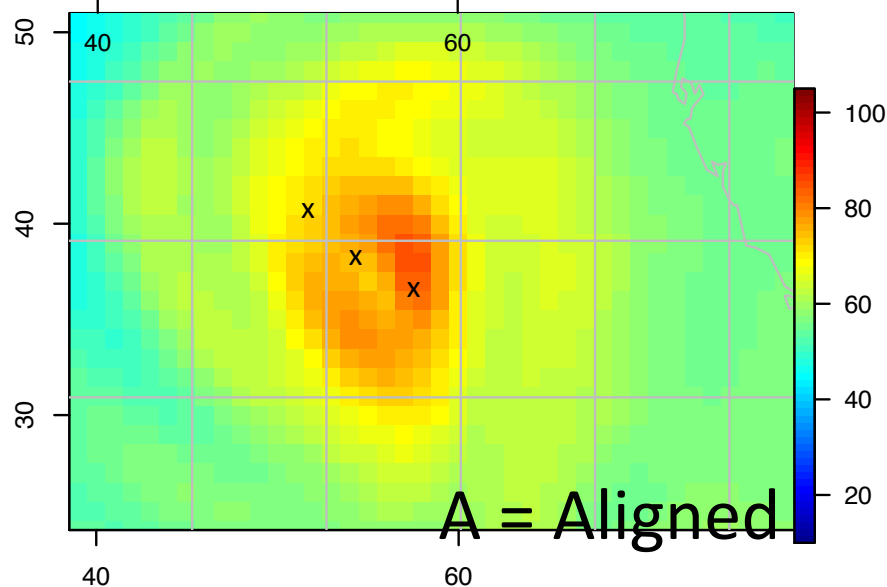
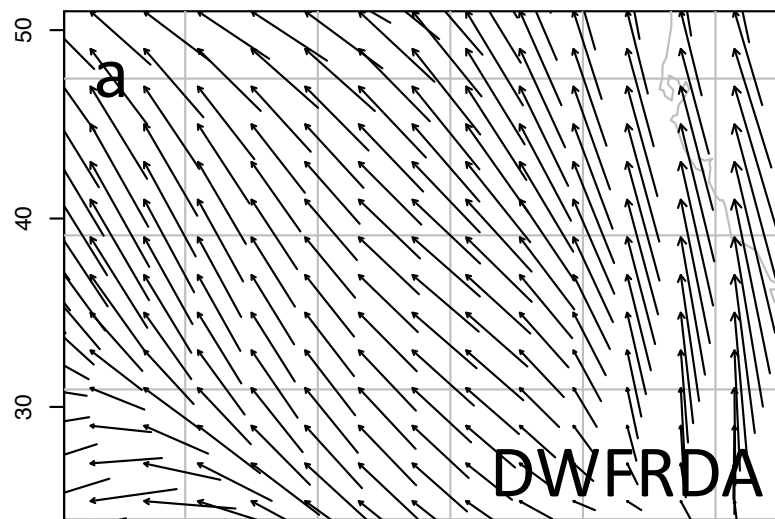
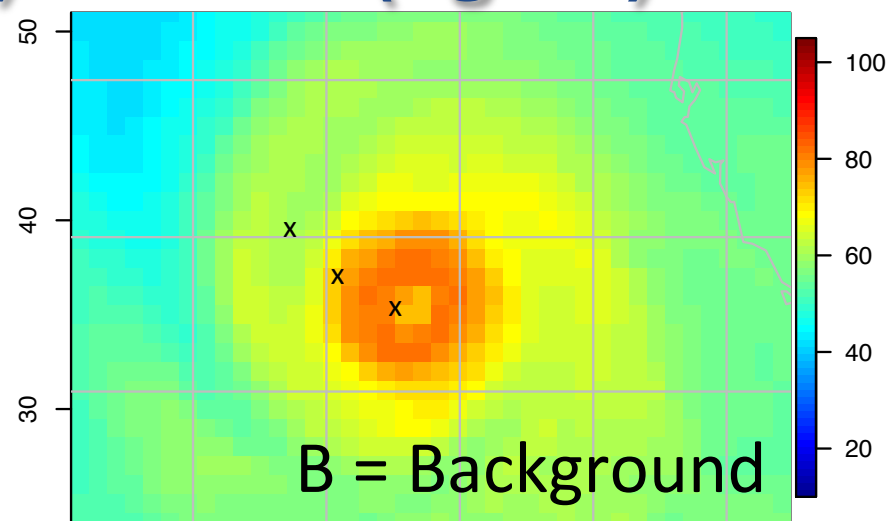
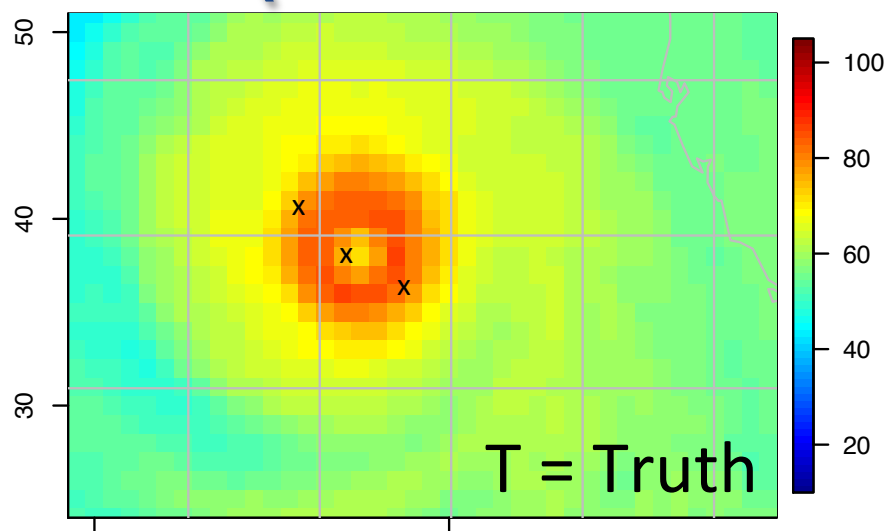




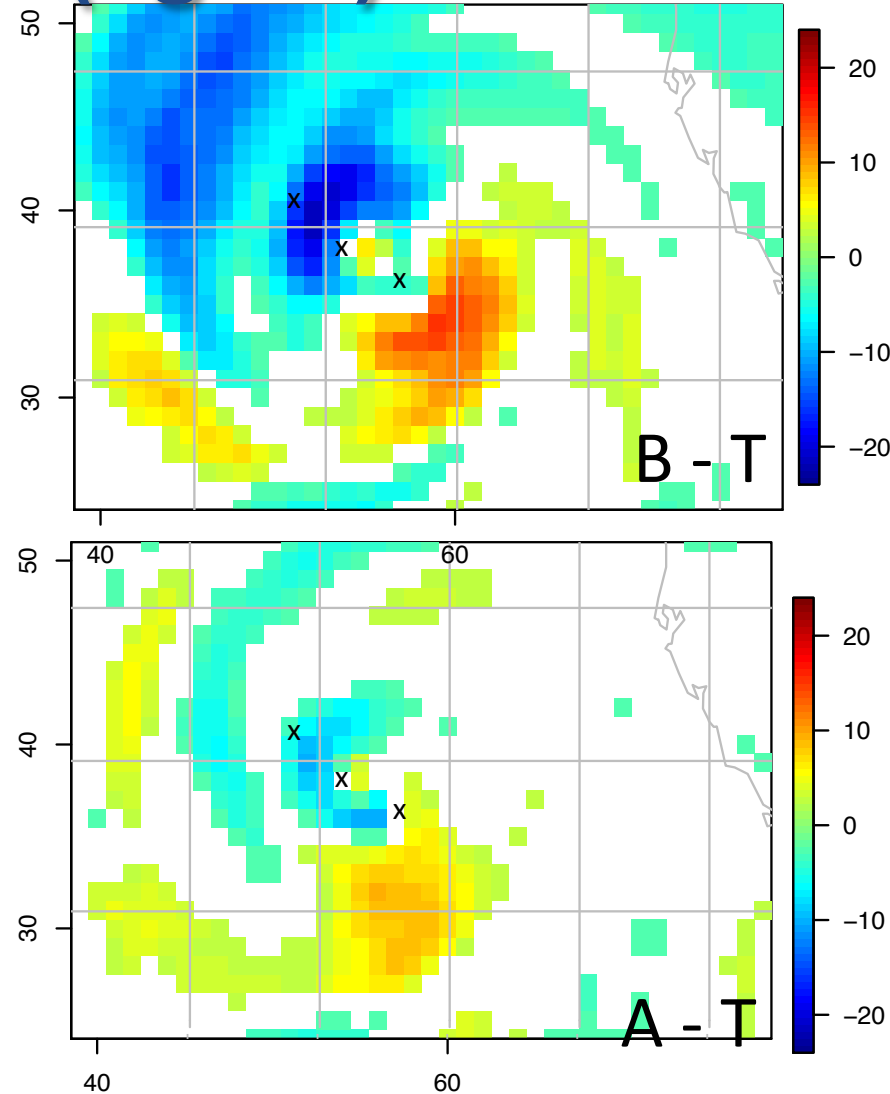
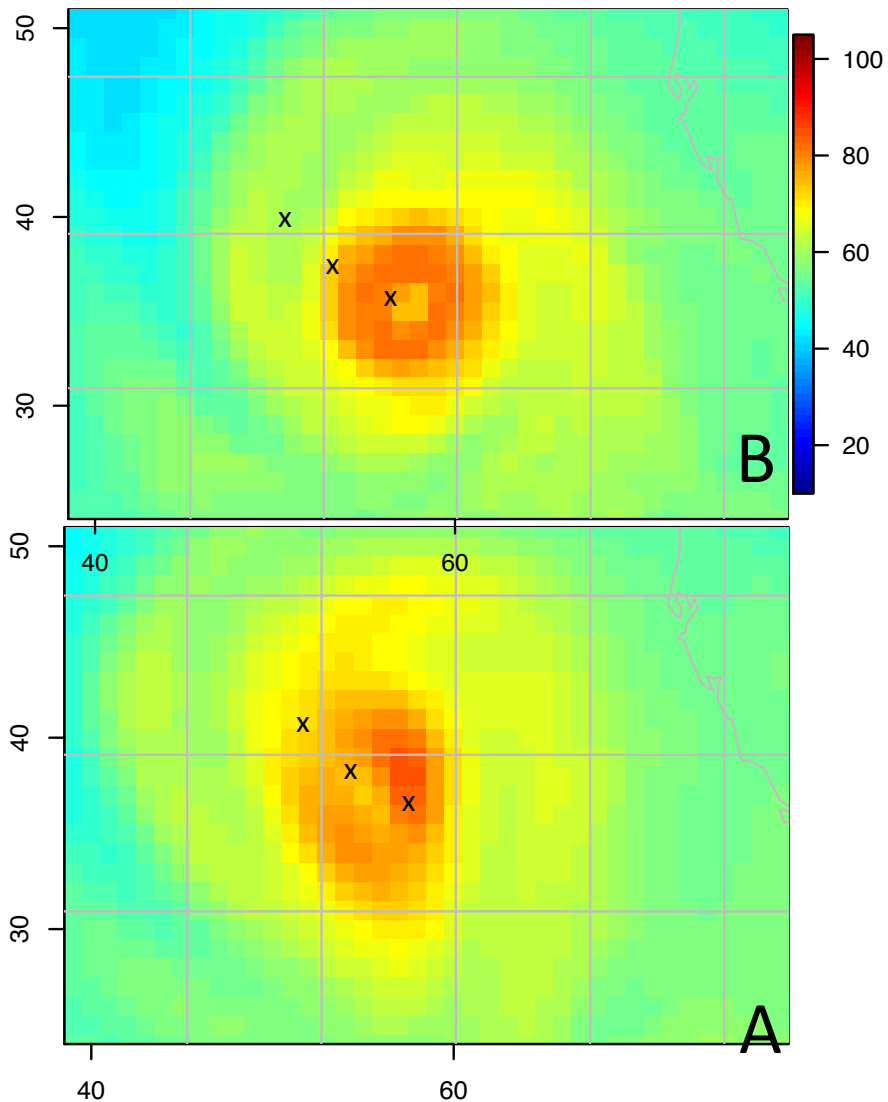




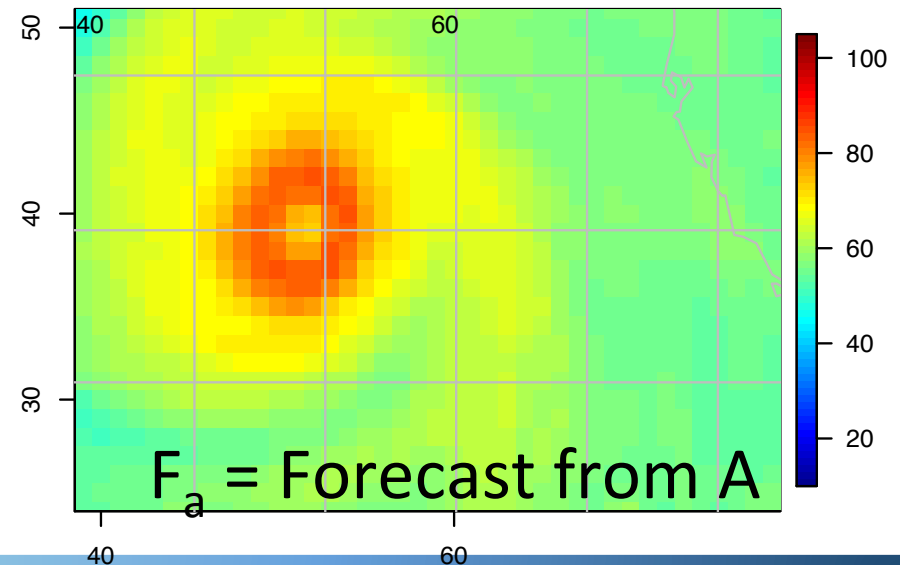
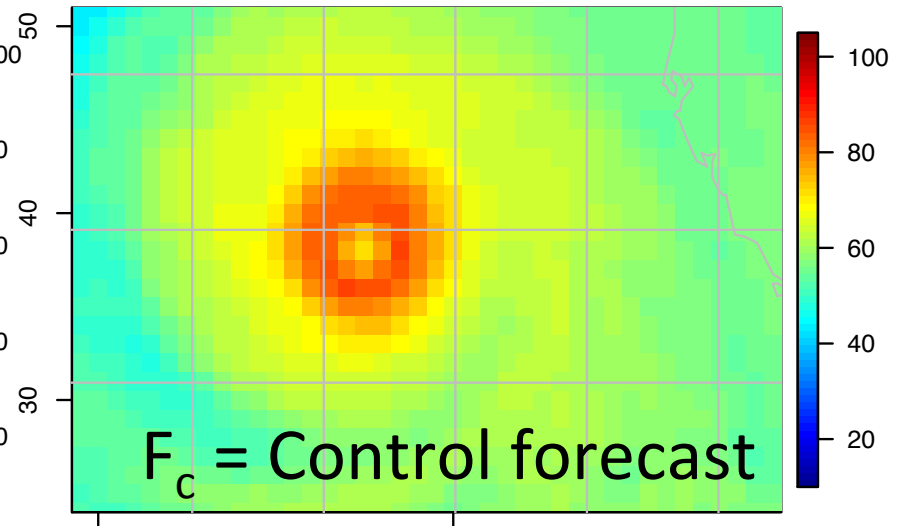
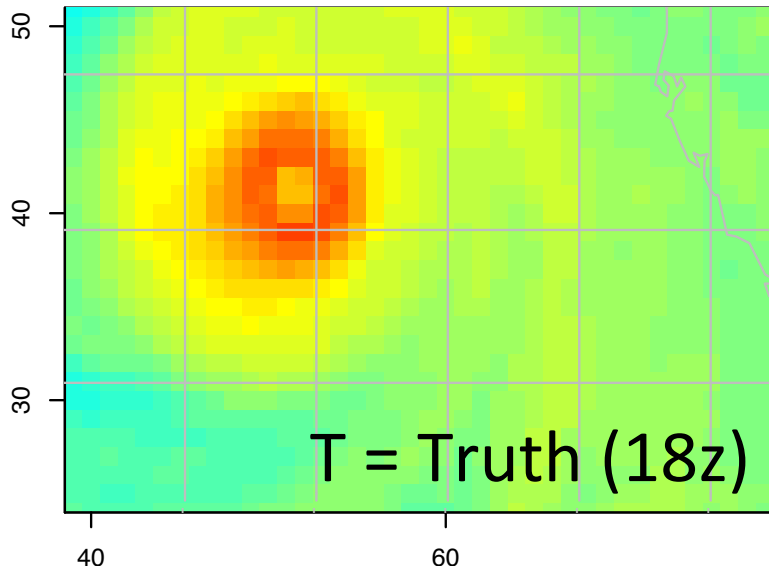
dWRF (FCA via WRFDA) for IWV (kg/m^2)



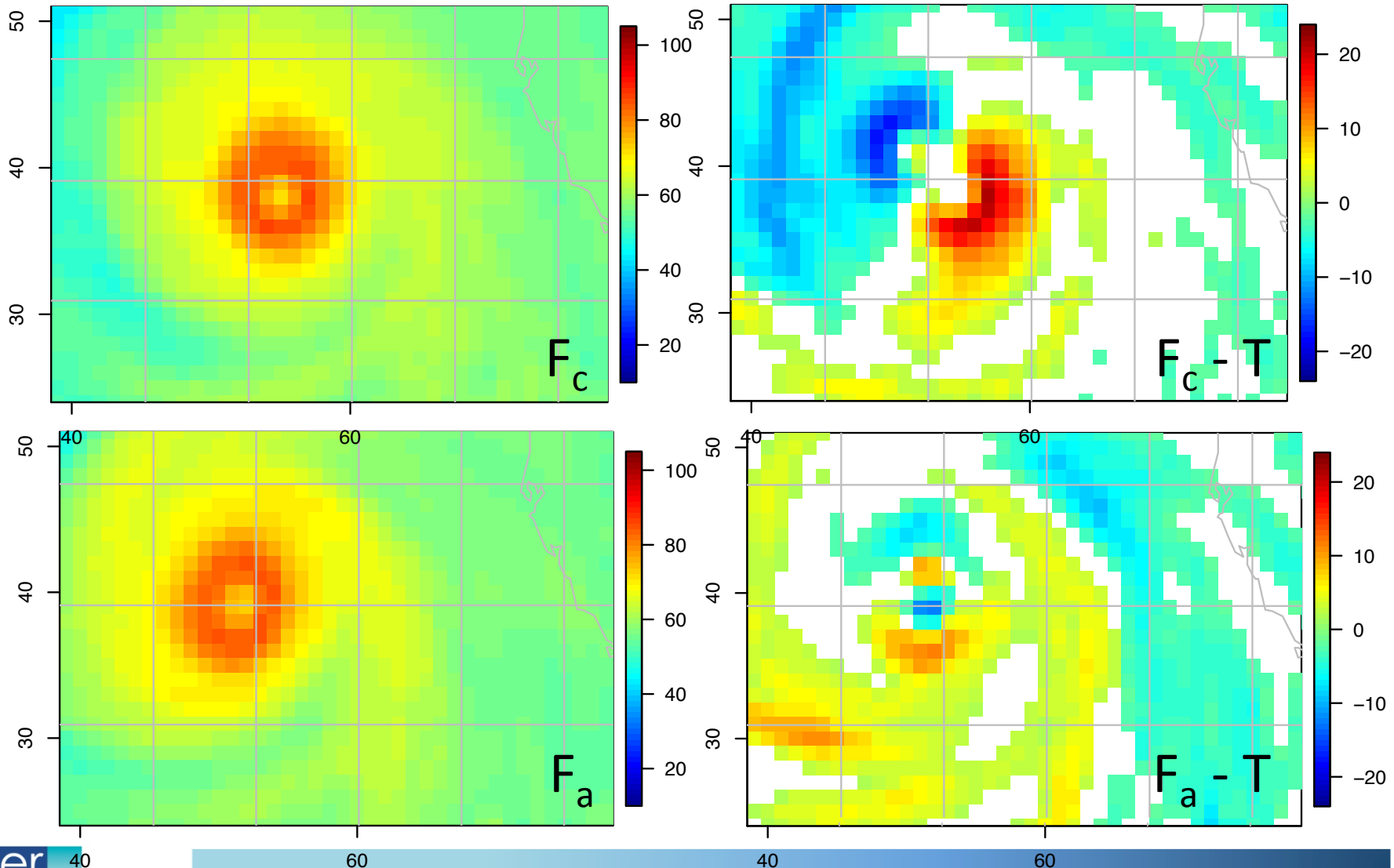
Katrina dWRF for IWV (kg/m^2)



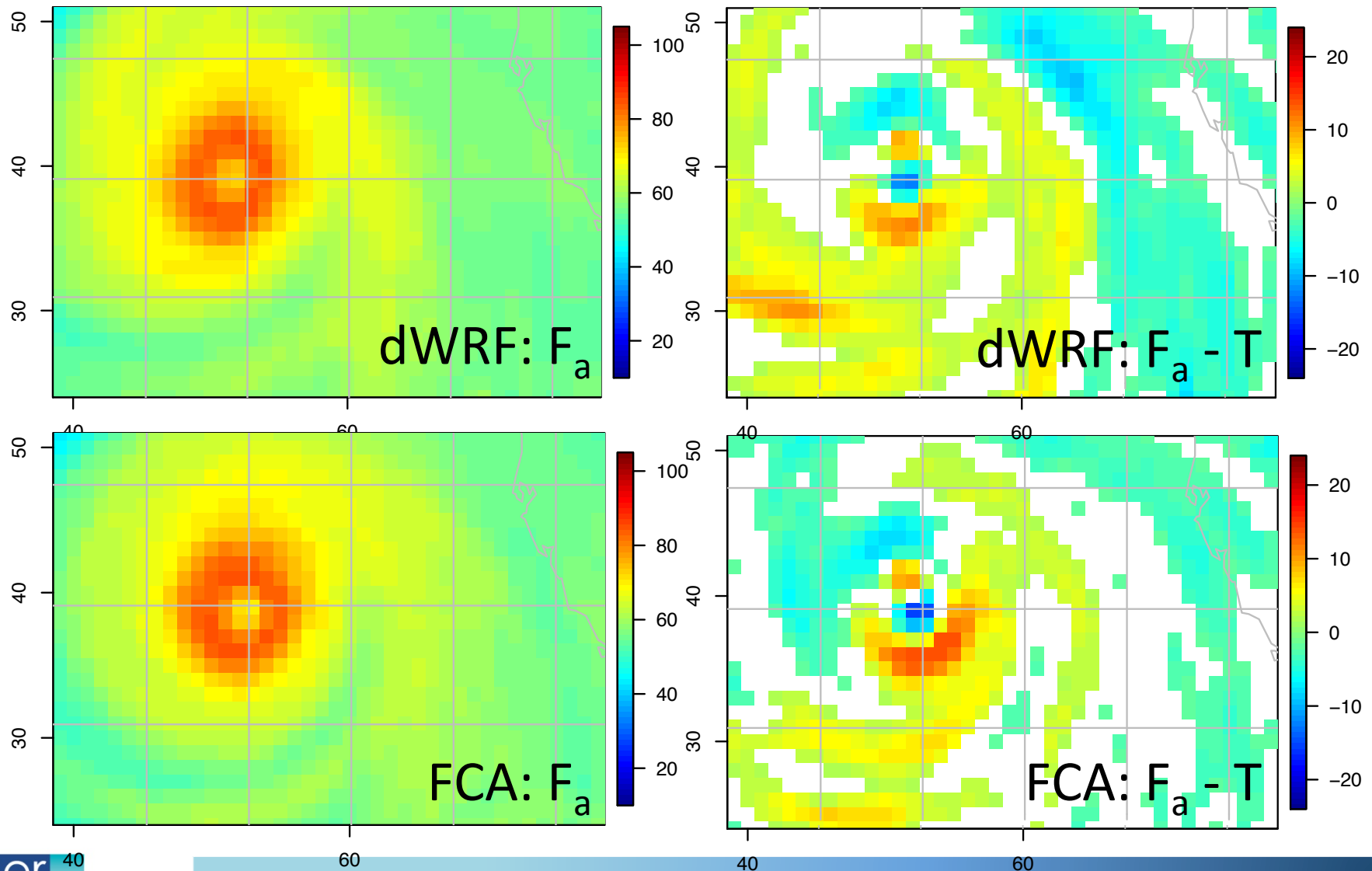
Katrina dWRF 6-h forecasts IWV (kg/m^2)



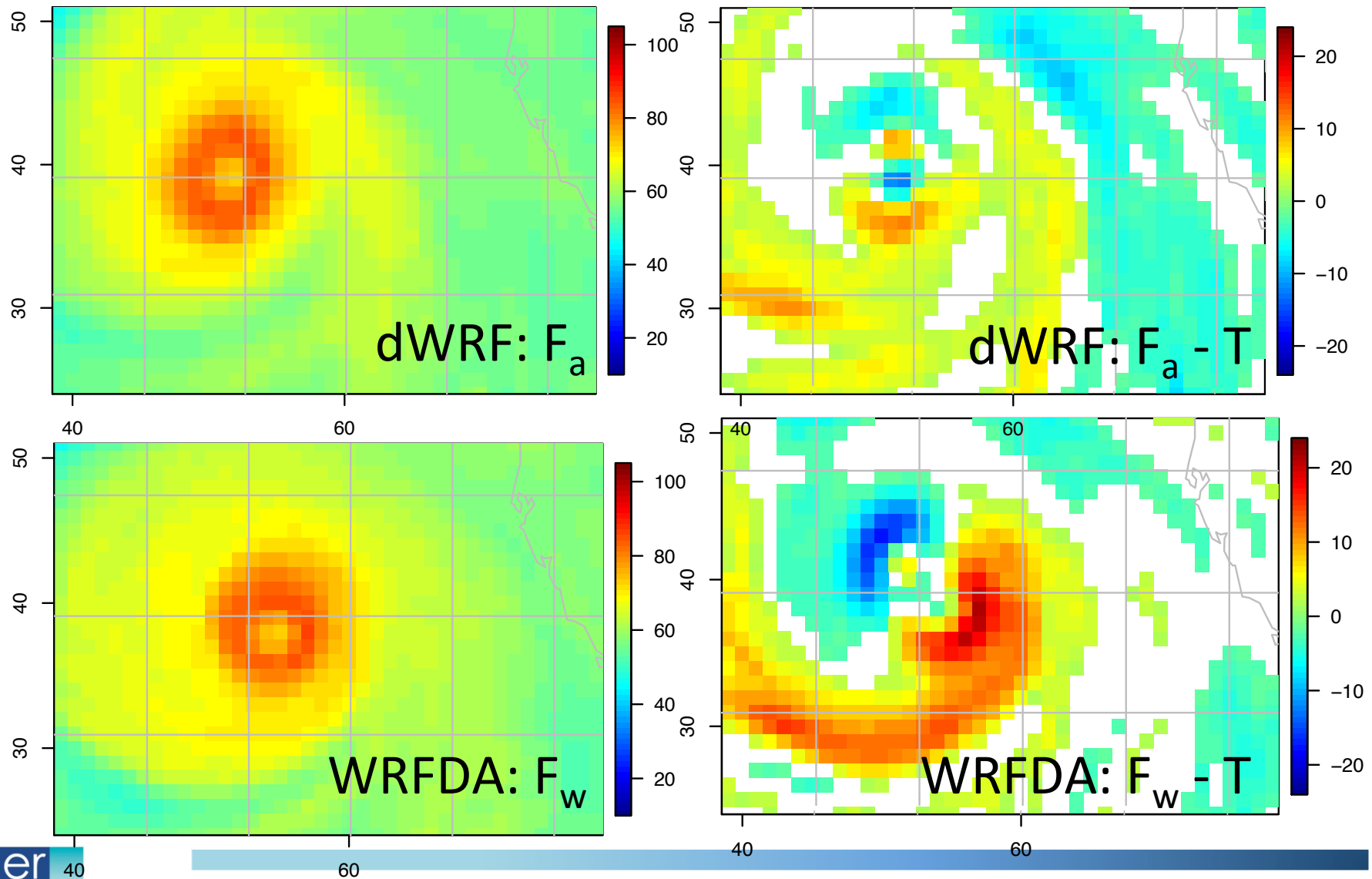
Katrina dWRF 6-h forecasts IWV (kg/m^2)



Katrina dWRF/FCA 6-h forecasts IWV



Katrina dWRF/WRFDA 6-h forecasts IWV

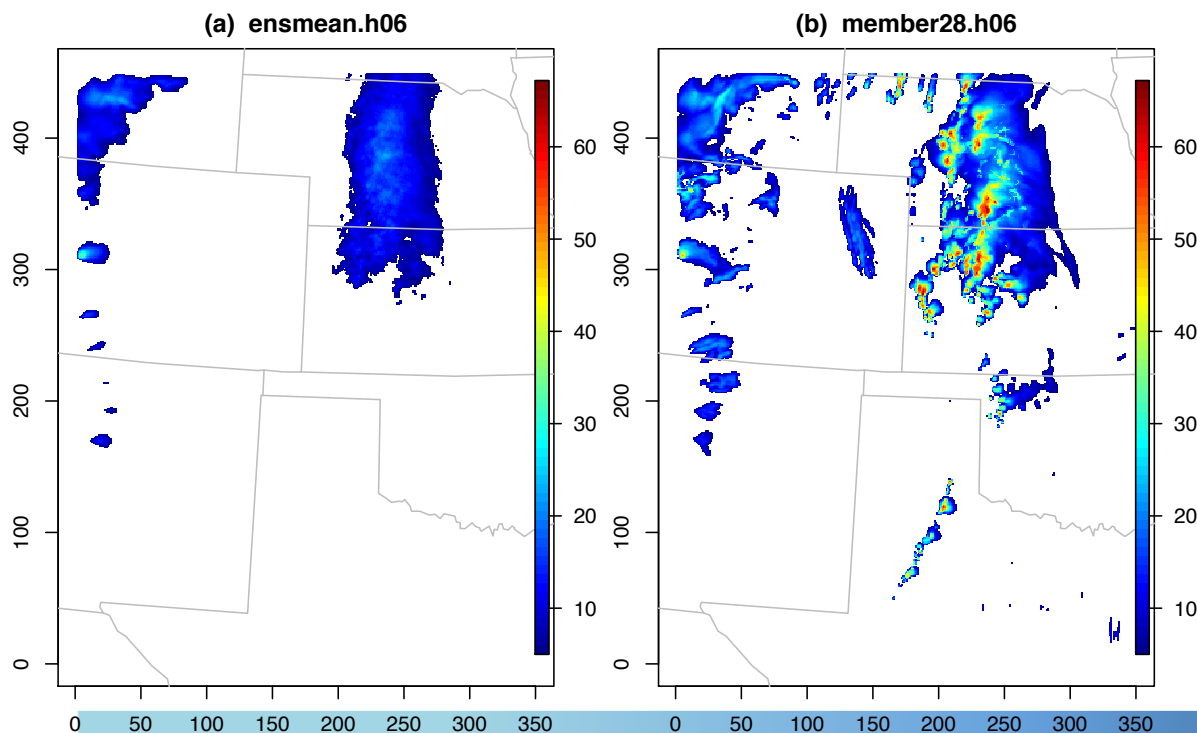


Conclusions

- 2d FCA displacements can be applied to a full model state
- Standard 3dVAR of u and v can be hijacked to yield displacements
 - Nominal covariances for u and v are satisfactory in TC case
- Using GPS PW data in dWRF results in
 - comparable forecast improvement relative to using IWV in stand alone FCA
 - much better forecast improvement than using IWV in standard WRFDA 3dvar
- FCA can explain a sizeable fraction ($>10\%$) of variance for a background ensemble of radar observations (dBZ)

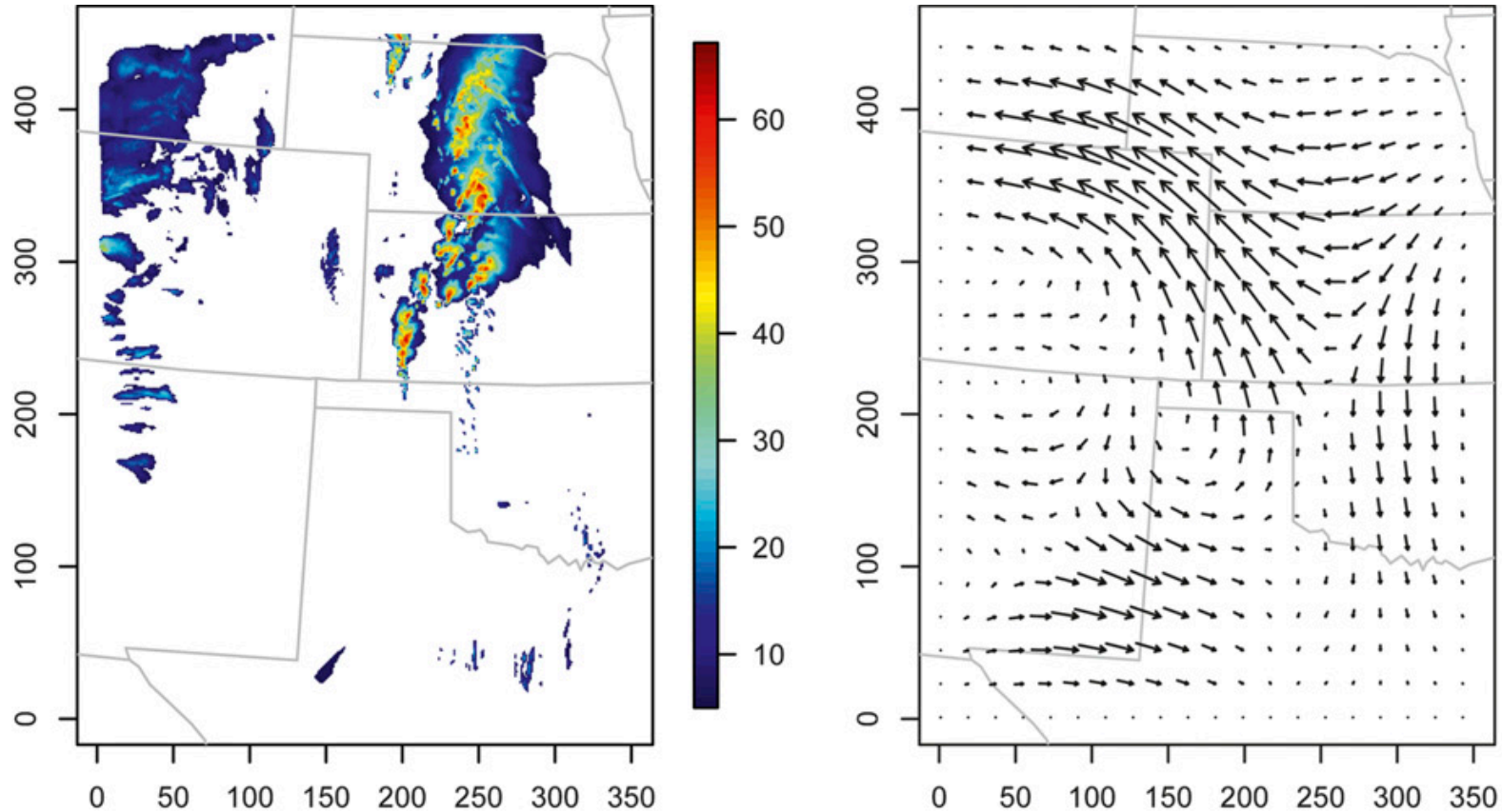
FCA and ensemble errors for composite reflectivity (dBZ)

- FCA reduces variance and increases spatial scales of errors
- 30 member background ensemble of 6-h 3-km WRF forecasts valid 04 UTC 28 Mar 2007
- Use ensemble median in place of ensemble mean to preserve small scale detail



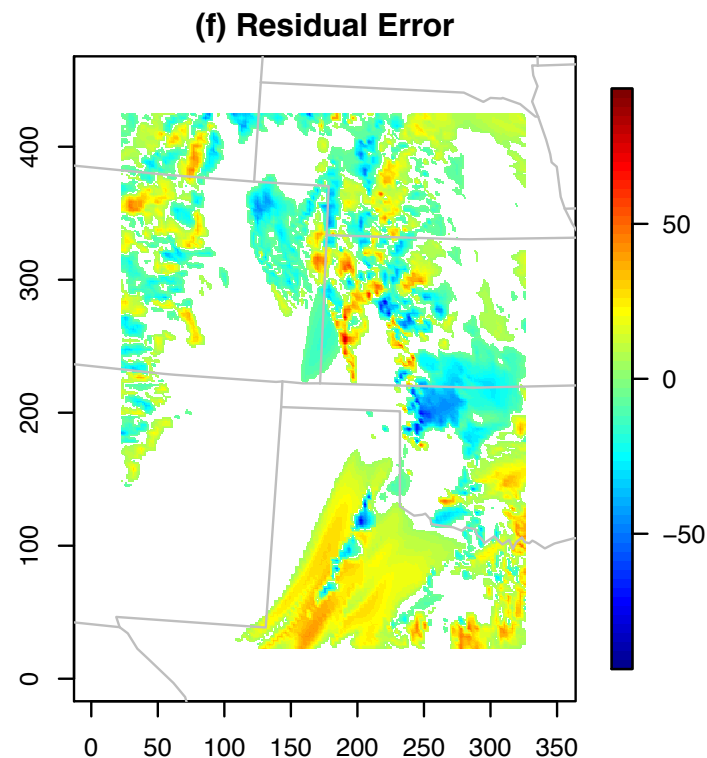
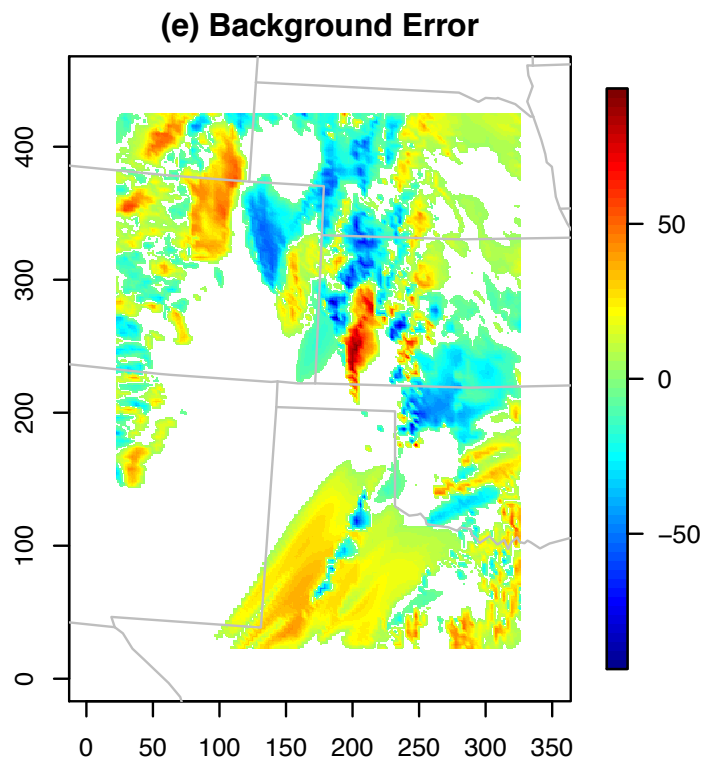
FCA and ensemble errors for composite reflectivity (dBZ)

- Use FCA to displace each ensemble member, using the ensemble median member as “truth”



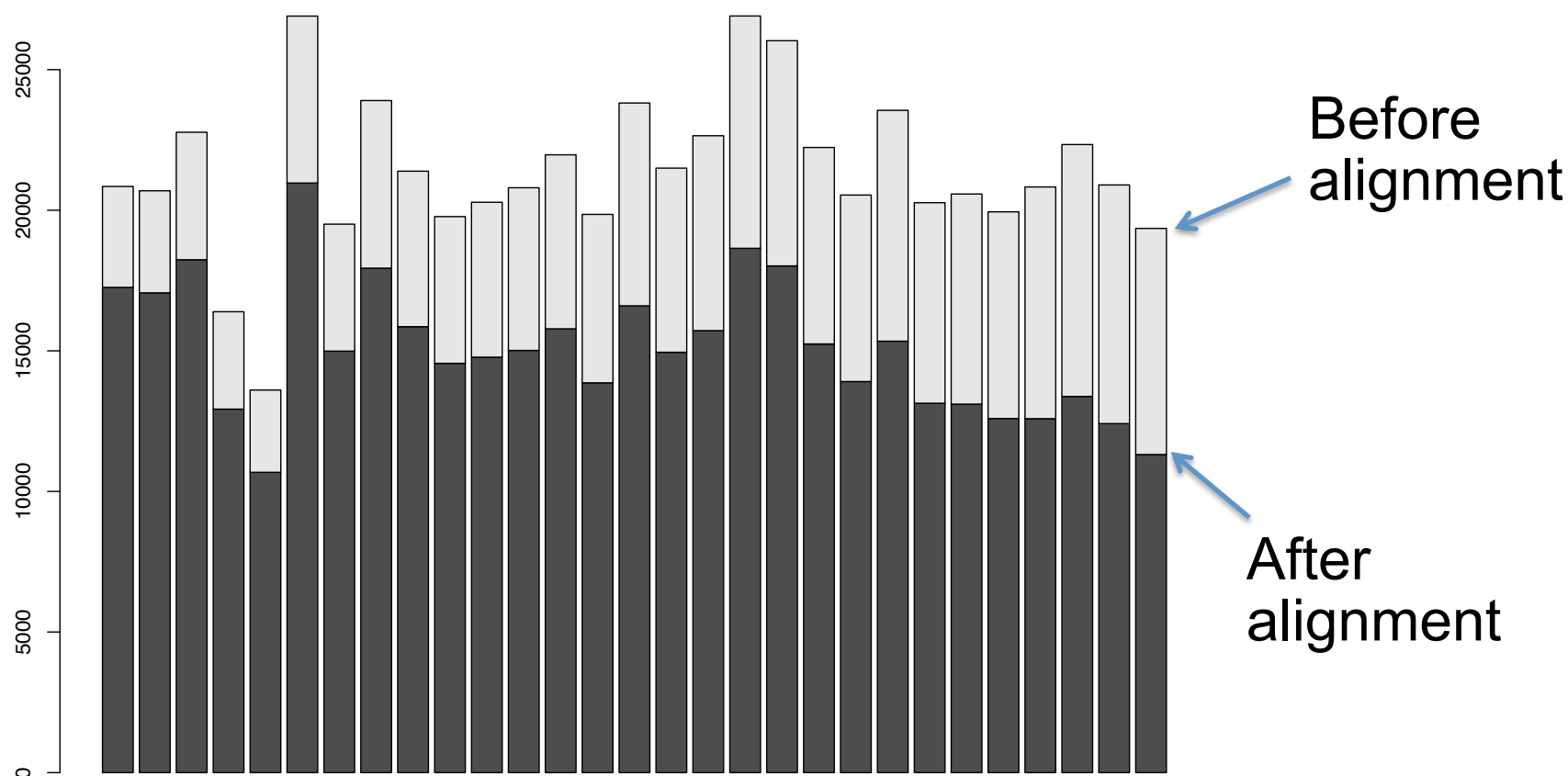
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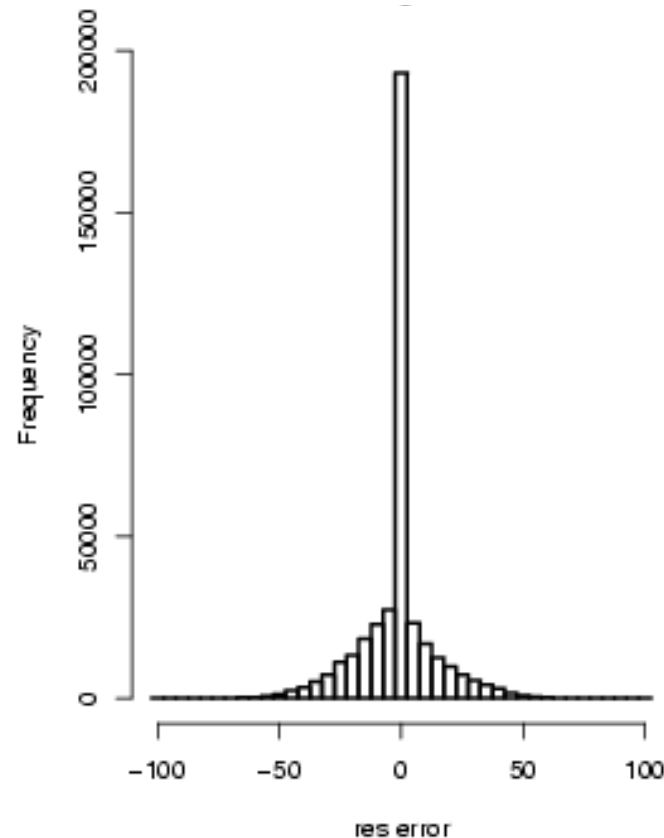
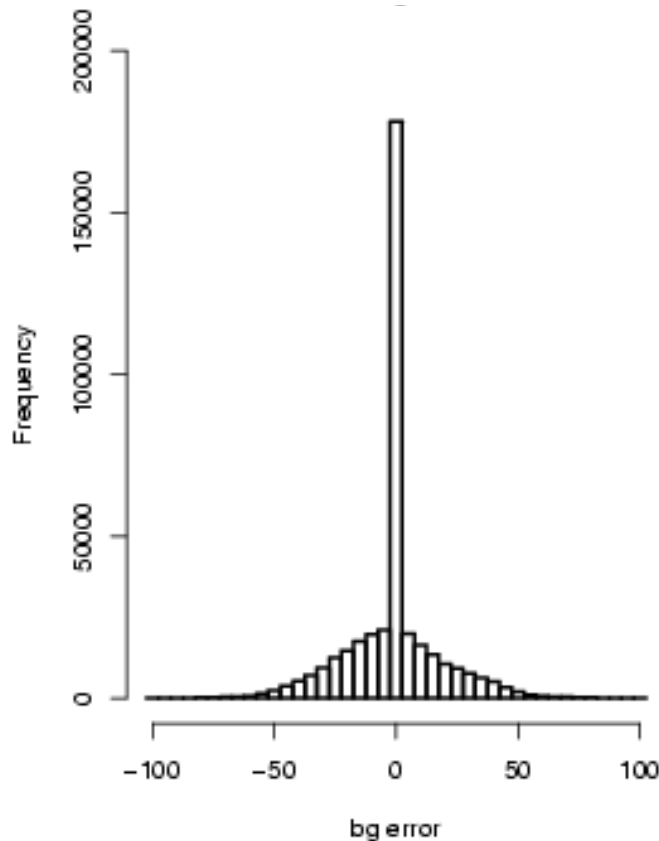
FCA and ensemble errors for composite reflectivity (dBZ)

- FCA reduces distance from median for each ensemble member (by varying degrees)



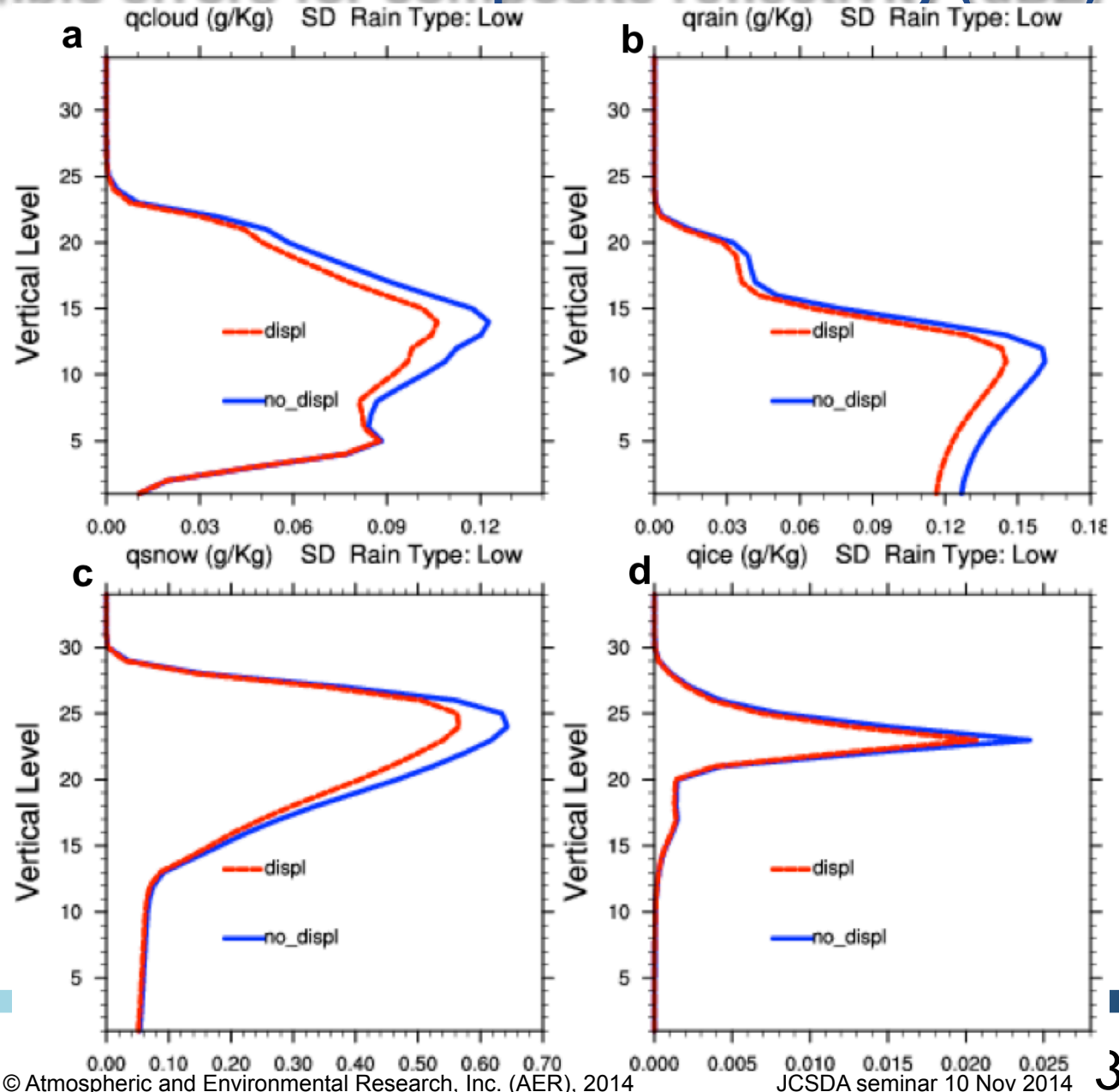
FCA and ensemble errors for composite reflectivity (dBZ)

- FCA reduces variance of dBZ:
 - thinner tails



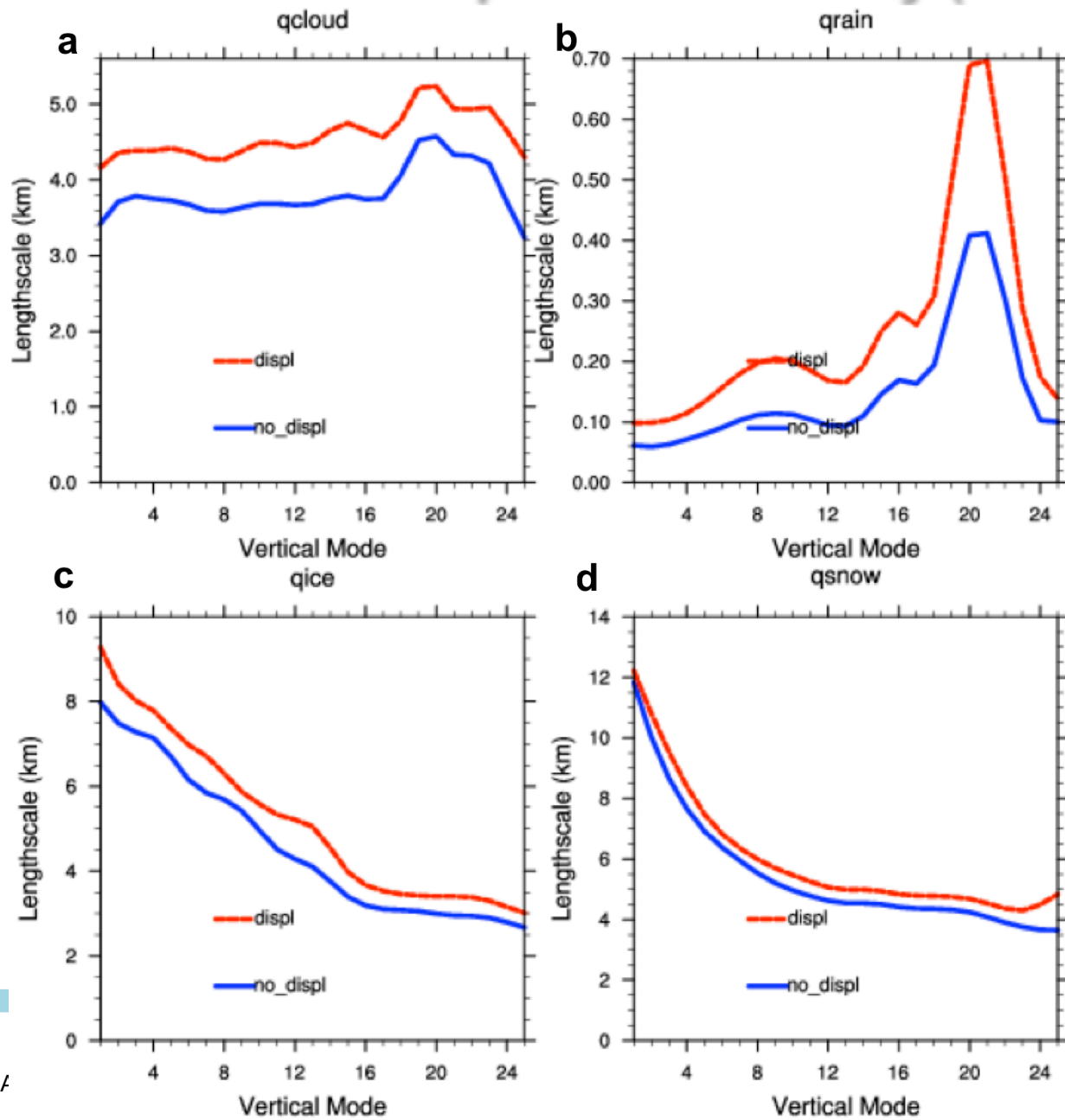
FCA and ensemble errors for composite reflectivity (dBZ)

FCA reduces
variance of
cloud liquid,
rain, ice, snow



FCA and ensemble errors for composite reflectivity (dBZ)

FCA increases correlation length scales



Conclusions

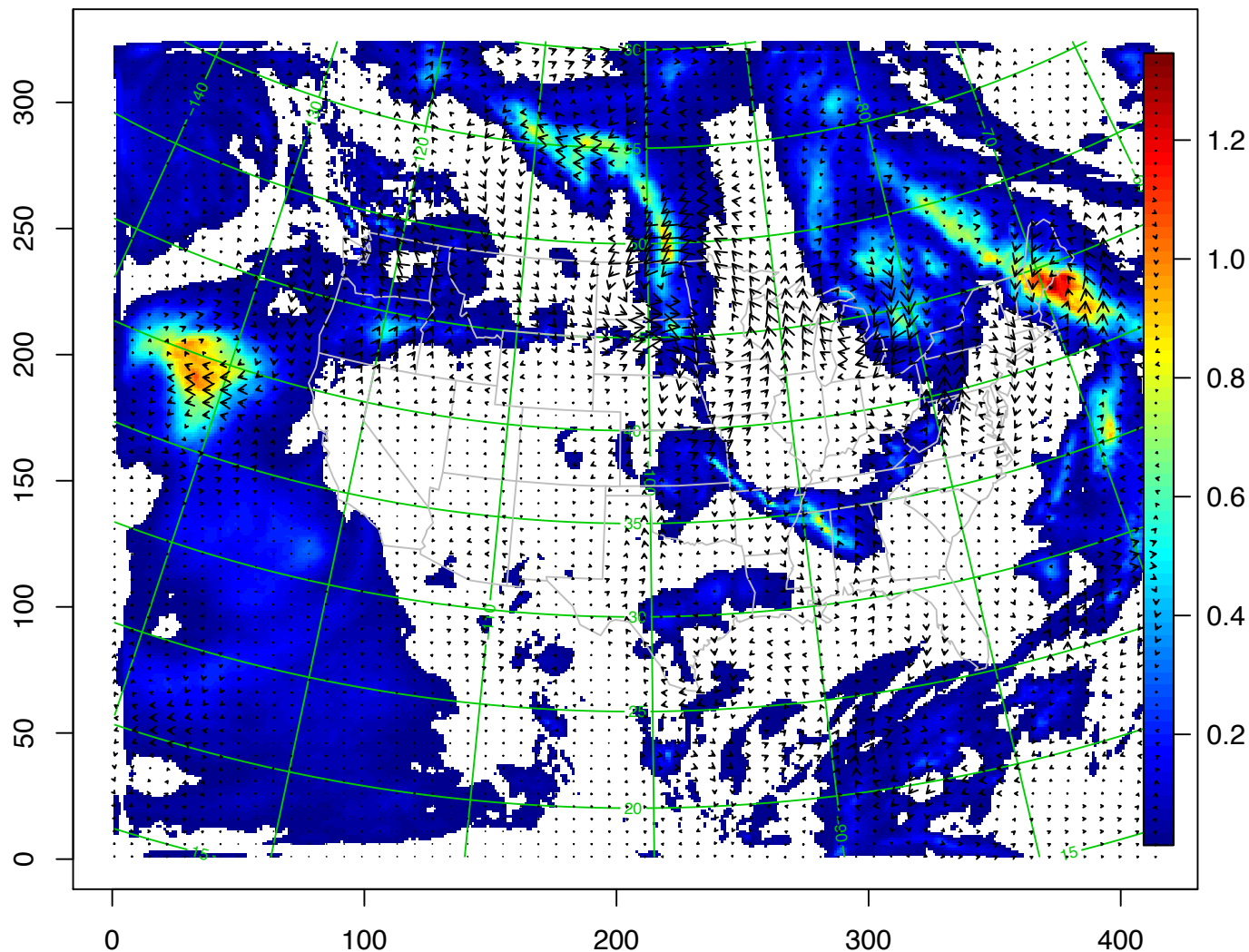
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- FCA can explain a sizeable fraction ($>10\%$) of variance for a background ensemble of radar observations (dBZ)

dWRF application to imagery data

- Uses a short-term, moderate resolution (15km) forecast over CONUS
- Example is from June 2006, using GOES-13 channels 2-5

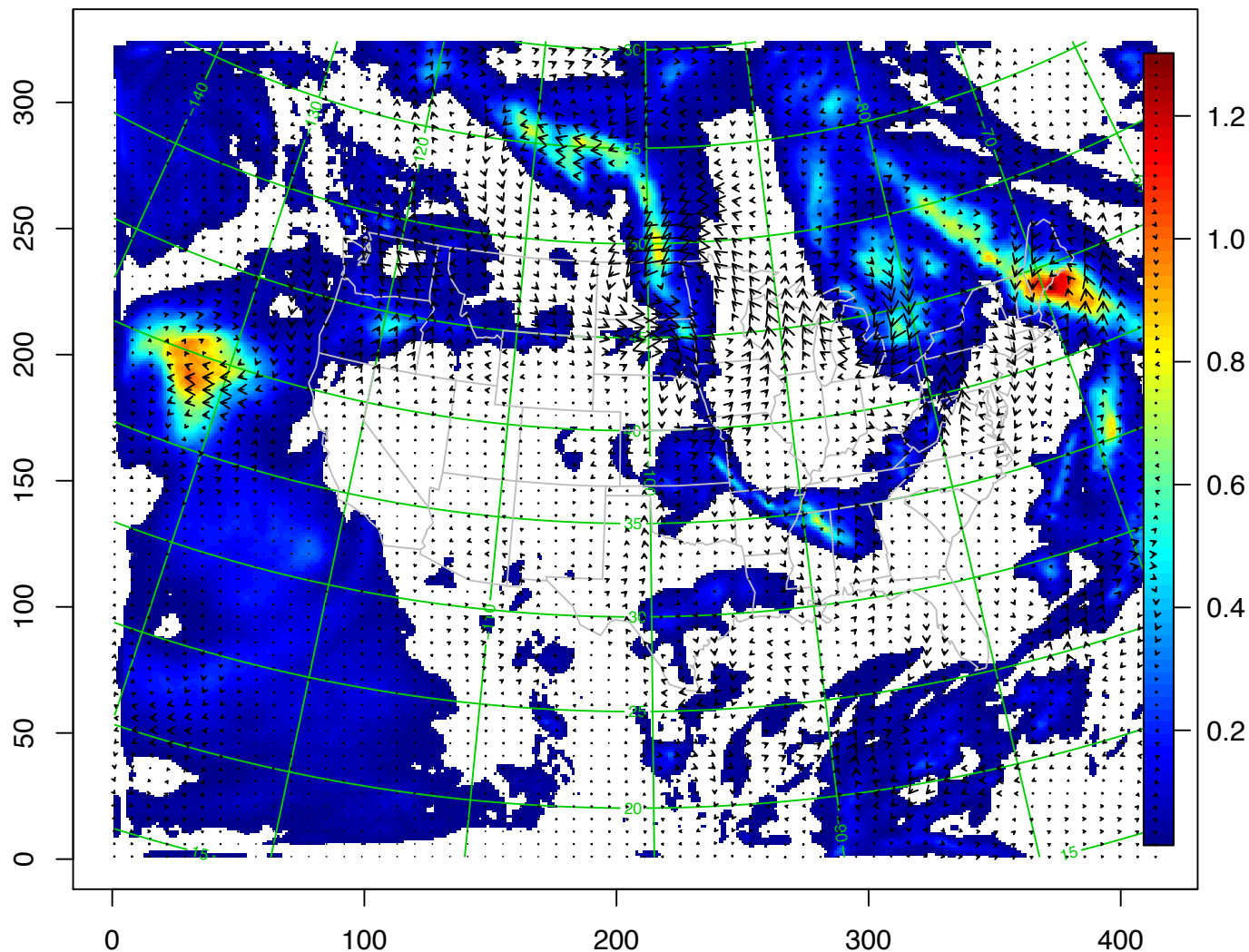
dWRF application to imagery data

run03C_20140820_scale3 fg cld

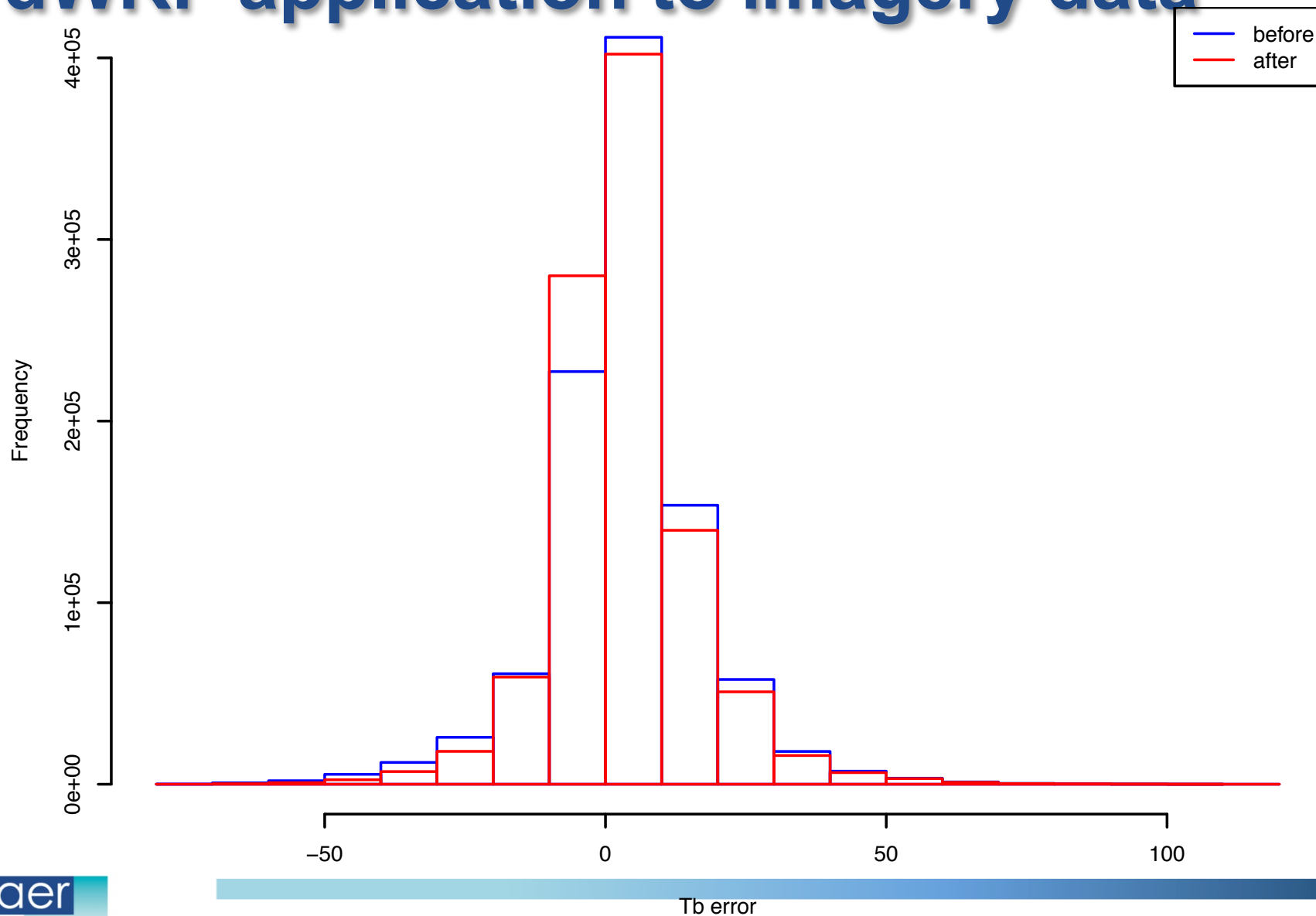


dWRF application to imagery data

run03C_20140820_scale3 anal cld



dWRF application to imagery data



Future work

- Tune / Derive background error covariances for displacement vectors
 - Explore “coalescence” (Ravela 2012)
- Extend control vector for simultaneous application of additive/displacement corrections
- Improve short-term cloud forecasting with 2-h cycle of WRFDA using GEO imagery in dWRF

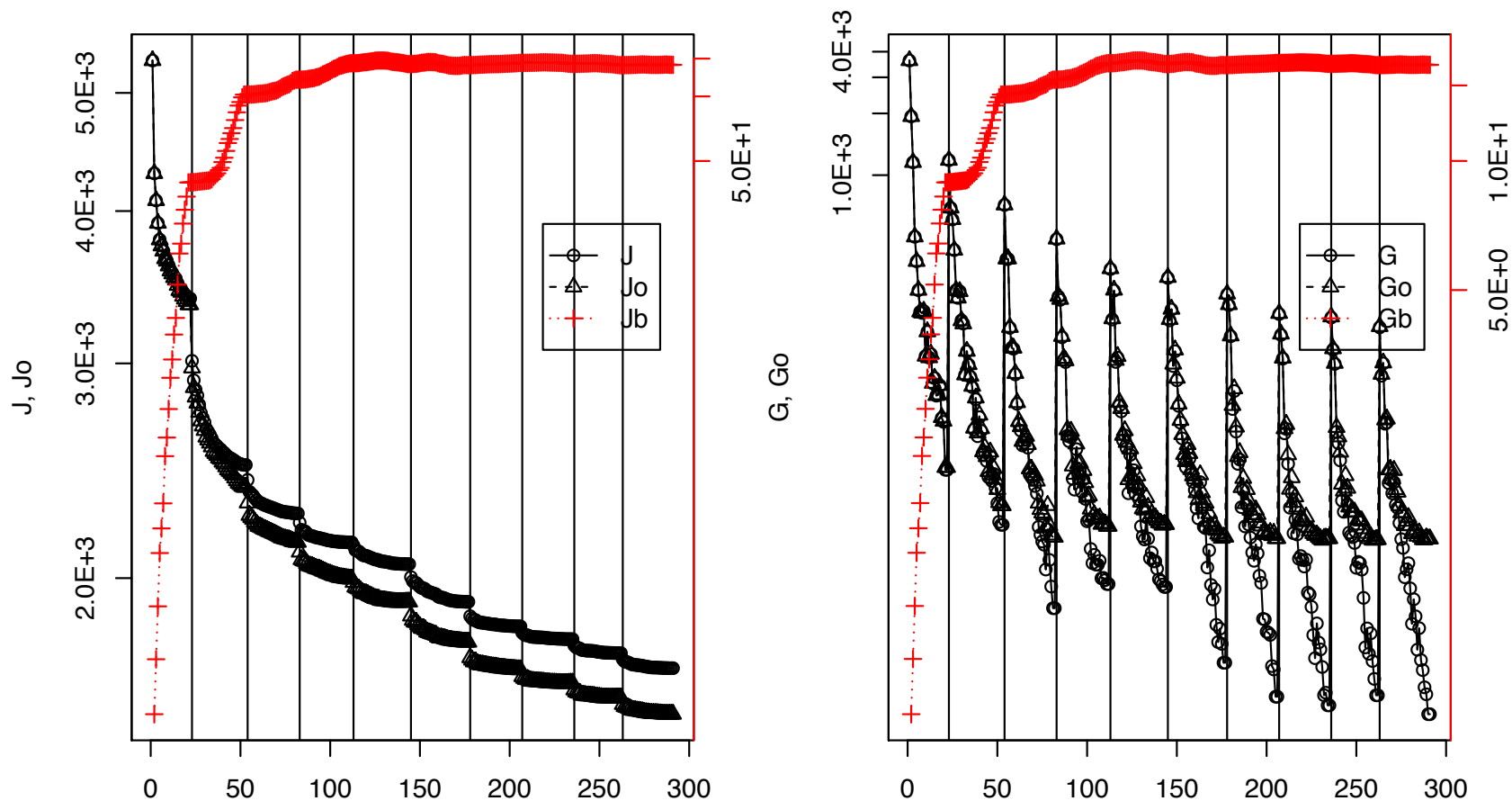
Thank you

- Support from USAF as part of NCAR's advanced cloud analysis and forecast system (ACAPS)
- Grassotti et al., 1999, JAMC, [doi:10/fprb35](https://doi.org/10.1029/1998JD10355)
- Hsiao et al., 2010, MWR, [doi:10/bktnst](https://doi.org/10.1175/2009JCLI3501)
- Nehrkorn et al., 2014, MWR, [doi:10/p5d](https://doi.org/10.1175/JCLI1210.1875)
- tnehrkor@aer.com

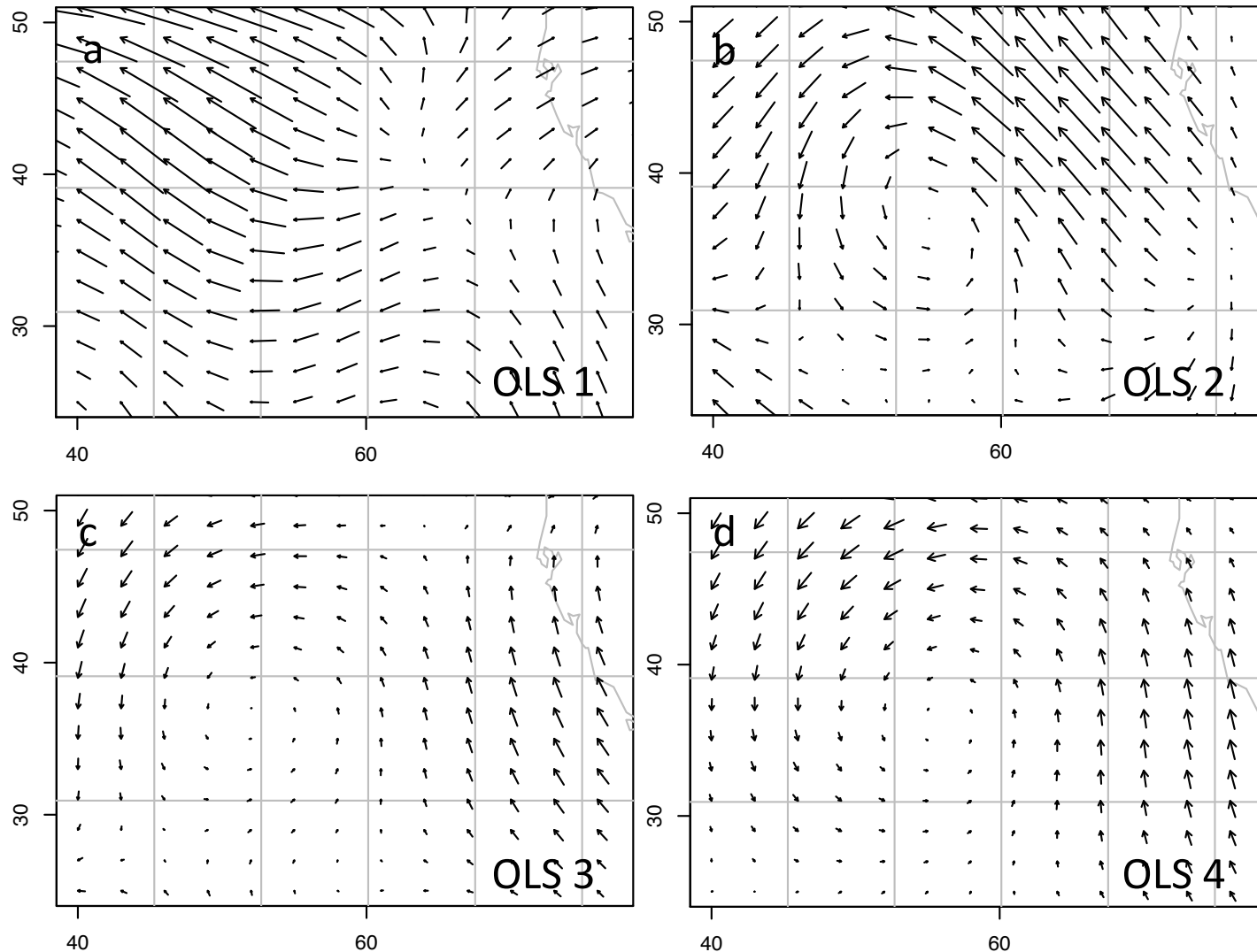
Backup slides

- More results dWRF FCA

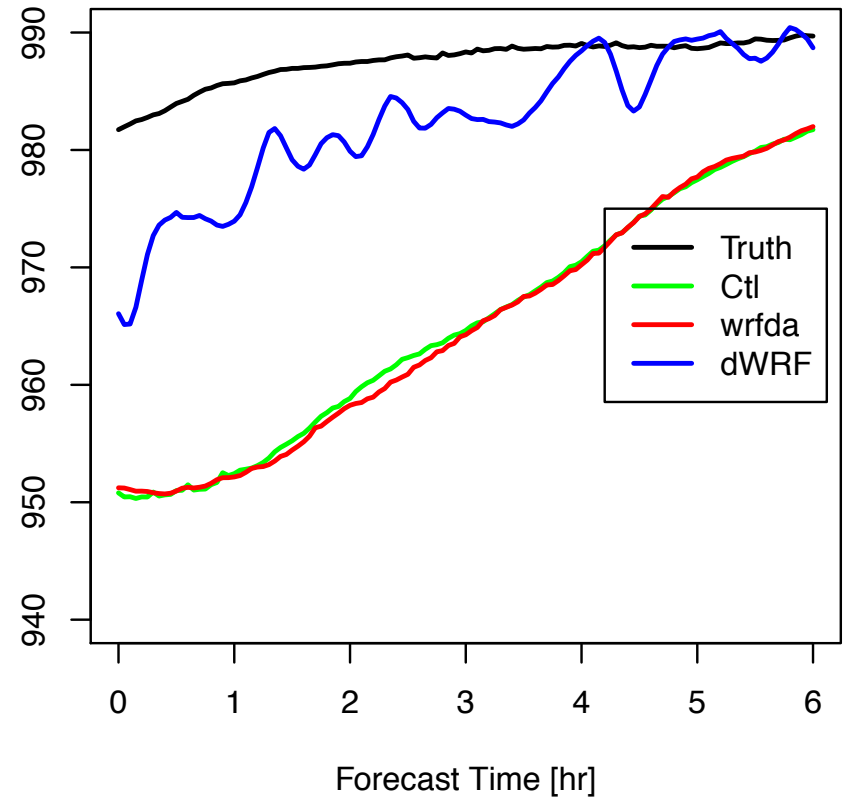
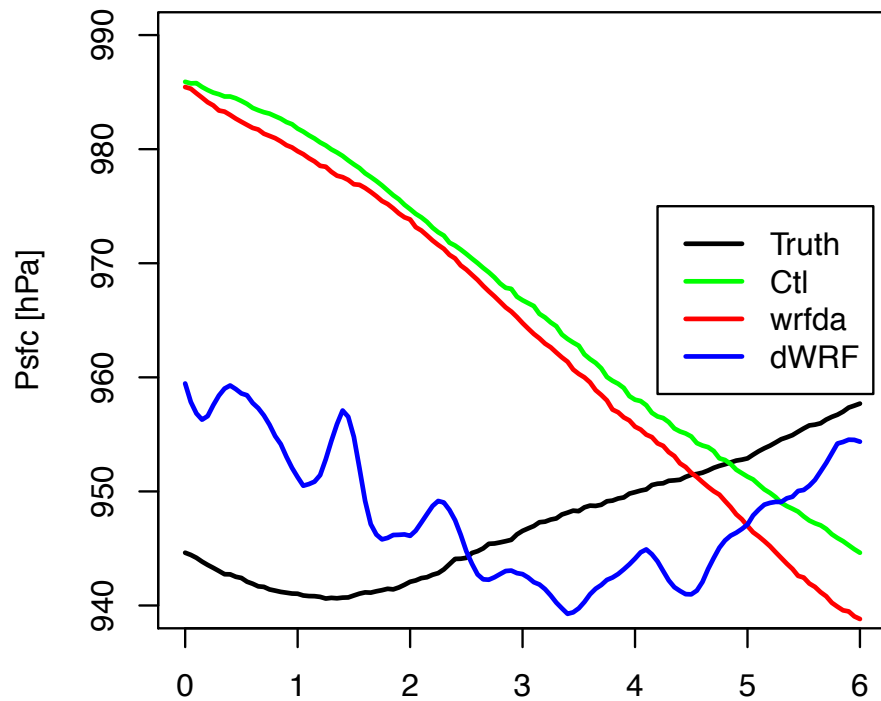
dWRF convergence behavior



Katrina dWRF incremental displacements



Katrina forecast evolution of Psfc



dWRF/WRFDA analysis/forecast errors

dWRF WRFDA dWRF WRFDA

Type	Dens	Bord	OLS	RMSE			
				A	A _w	F _A	F _w
IWV	3	5		2.95	1.88	3.84	5.81
IWV	3	10		2.71	1.83	3.99	5.87
IWV	5	5		3.23	3.79	3.41	5.35
IWV	5	10		3.26	3.79	3.78	5.34
IWV	10	5		4.81	6.15	5.50	5.49
Raob	3	5		4.26	2.22	2.97	2.64
Raob	3	10		4.23	2.23	2.95	2.94
Raob	5	5	8	3.82	3.83	3.04	3.35
Raob	5	10	8	3.87	3.82	3.10	3.31
Raob	10	5	1	3.72	6.22	3.17	6.48