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Spring Colloquium on
'Regional Weather Predictability and Modeling'
April 11 - 22, 2005

1) Workshop **on Design and Use of Regional Weather Prediction Models,** *April 11 - 19*

2) Conference on **Current Efforts Toward Advancing the Skill of Regional Weather Prediction. Challenges and Outlook,** *April 20 - 22*

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Data Assimilation in Regional Modeling & Prediction
Lecture II

Applications of 4DVAR & Ensemble KF Techniques

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Data Assimilation in Regional Modeling and Prediction

Lecture II

Applications of 4DVAR and Ensemble KF techniques

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Currently used data assimilation techniques in NWP

- 4DVAR
  - Operational versions: ECMWF, British and French Met Offices
  - Research versions in USA at NCAR, CSU, NCEP and FSU
- Ensemble KF
  - Used for operational NWP in Canada
  - Research versions in USA at NCAR, NOAA and CSU

Basic properties of 4DVAR

Minimization of

$$F = \frac{1}{2}(H(X^t) - y)^T R^{-1}(H(X^t) - y) + \frac{1}{2}(\zeta^t - \zeta)^T B^{-1}(\zeta^t - \zeta) + \varepsilon_X^T Q^{-1}\varepsilon_X$$

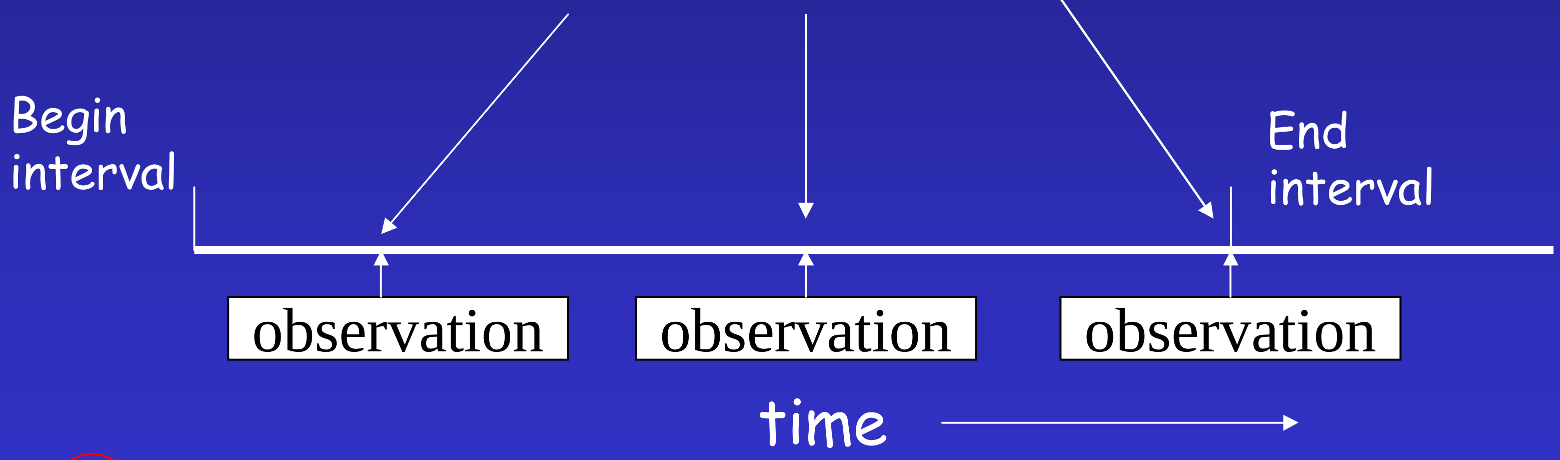
is performed by

1. Evaluating directional gradients of F with respect to control parameters, $\frac{\partial F}{\partial \zeta}$ and $\frac{\partial F}{\partial \varepsilon_X}$
   - The gradients are computed using ADJOINT model
2. The gradients are then used in iterative minimization algorithms to find the optimal ζ

4DVAR assimilation procedure

$$y = H(X^t) + \varepsilon_y$$ Observation errors

$$X_\tau^t = M(X_{\tau-\Delta\tau}^t) + G(\varepsilon_x)$$ Model errors



$$F = \sum_{time} \frac{1}{2}(H(X^t) - y)^T R^{-1}(H(X^t) - y) + \frac{1}{2}(X^t - X)^T B^{-1}(X^t - X)$$

Basic properties of EnKF

$$\overline{X_k^e} = \overline{X_k^f} + K(X_k^o - H\overline{w_k^f})$$

$$\overline{X_k^f} = N^{-1}\sum_{n=1}^{N} X_{kn}^f$$

Update of ensemble mean

$$P_k^f H^T = (N-1)^{-1}\sum_{n=1}^{N}(X_{kn}^f - \overline{X_k^f})(HX_{kn}^f - H\overline{X_k^f})^T$$

Update of covariance

$$K = P_k^f H^T (HP_k^f H^T + R)^{-1}$$

Kalman gain matrix

P_k^f Forecast error covariance matrix

- k is time index
- N is number of ensemble members; it varies depending on application
- EnKF is sequential algorithm

Examples

1. Estimation of cloud properties in 4D using cloud resolving model and high resolution geostationary satellite observations

2. Improvement of heavy precipitation forecast by assimilation of surface precipitation observations and estimation of model error

3. Convective system dynamical initialization using radar observations

EXAMPLE 1

Cloud properties in 4D from satellite observations

Vukicevic et al. (2005, JAS)

Motivation: Analysis of 3D structure and evolution of clouds is important for improved understanding of the role of clouds in the atmospheric system and for NWP of clouds and precipitation

- Data assimilation technique: 4DVAR with cloud resolving version of RAMDAS (Regional Modeling and Data Assimilation System, CIRA at Colorado State University)
- Observations : Geostationary Operational Environmental Satellites (GOES) imager IR brightness temperatures
- Case: Multi layered non-convective cloud evolution in south-central US

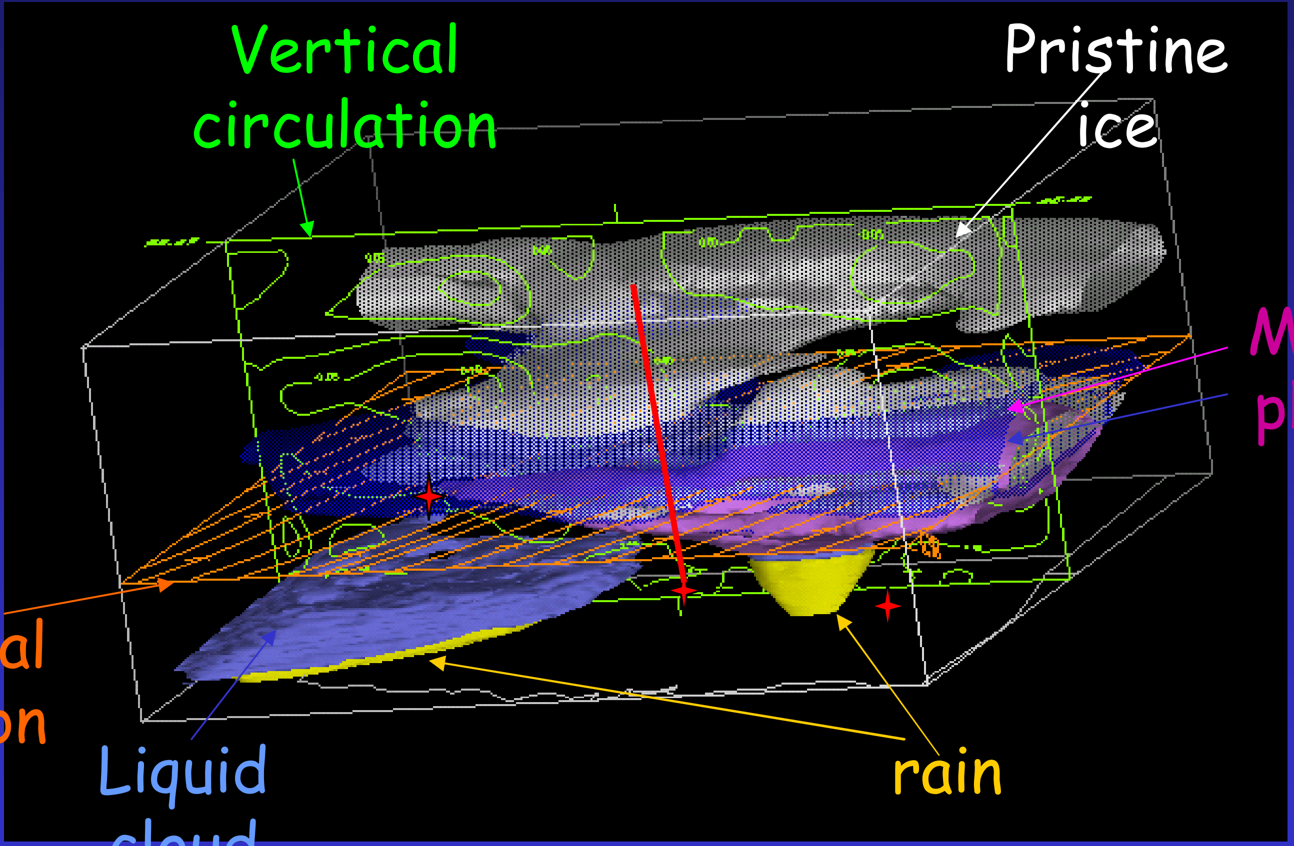
Cloud resolving model (CRM) properties

- Bulk, 2 moment cloud microphysics for ice: pristine ice, aggregates, snow, graupel and hail
- 1 moment for liquid: cloud droplets
- Prognostic mixing ratio and number concentration in 3D
- Assumed Gamma size distribution with prescribed width
- Nonhydrostatic dynamics
- Regional simulations with initial and boundary conditions from synoptic scale weather analysis

Downscaling from crude weather analysis

CRM simulation in 360000 km^2 by 17 km

domain started from crude 4D weather analysis



CRM simulation without data assimilation is not accurate but has skill

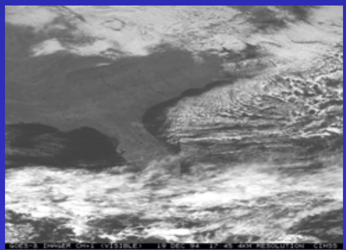
GOES imager observations

visible

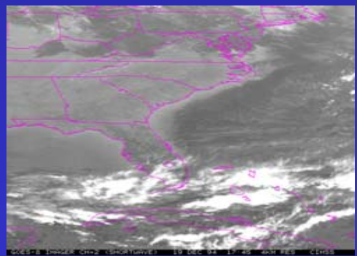
IR windows

GOES Channel		Wavelength (µm)	Central Wavelength (µm)	Detector Resolution (km)
1		0.52-0.72	0.7	1
2		3.78-4.03	3.9	4
3		6.47-7.02	6.7	8
3	G12	5.77-7.33	6.5	4
4		10.2-11.2	10.7	4
5		11.5-12.5	12.0	4
6	G12	12.9-13.7	13.3	8

15 minute data



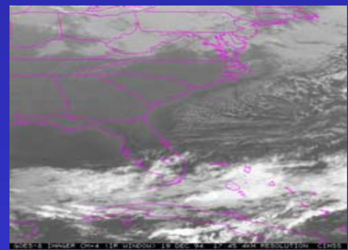
VIS



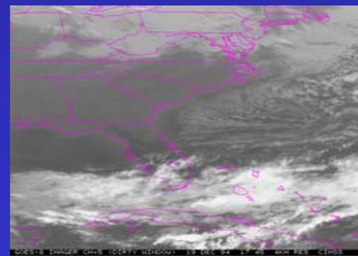
Near IR

Diff between ice and water clouds

IR water vapor



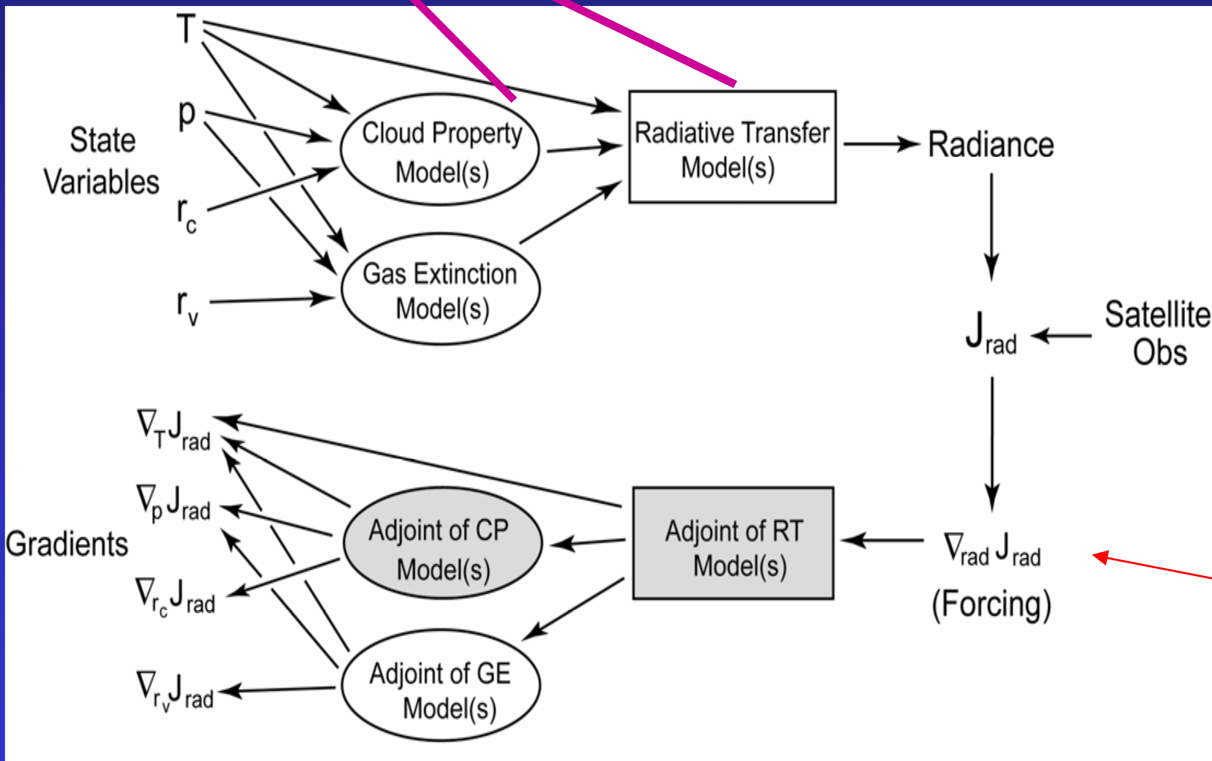
IR clouds and surface



IR clouds, surface and low level vapor

Transformation from the CRM into GOES observation space

$$y = H(X^t) + \varepsilon_y$$



Greenwald et al. (2003, MWR)

Gas absorption: OPTRAN (McMillin et al., 1995)

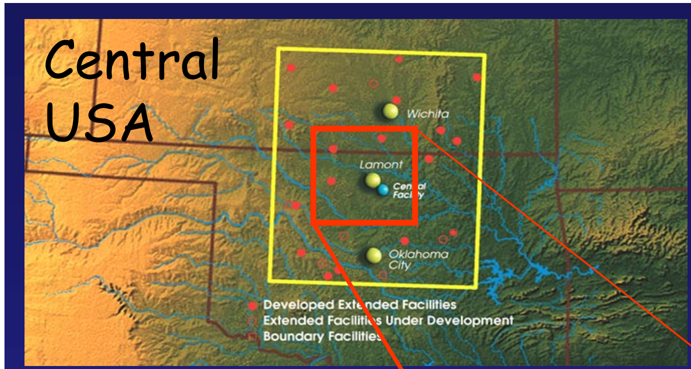
Cloud properties: Anomalous Diffraction Theory

Solar: SHDOM (Evans, 1998)

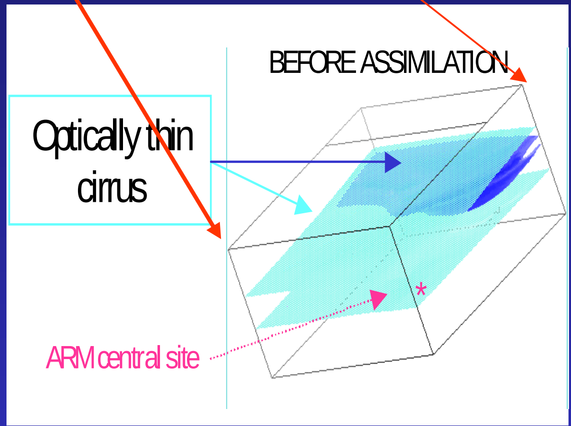
IR: Eddington two-stream (Deeter and Evans 1998)

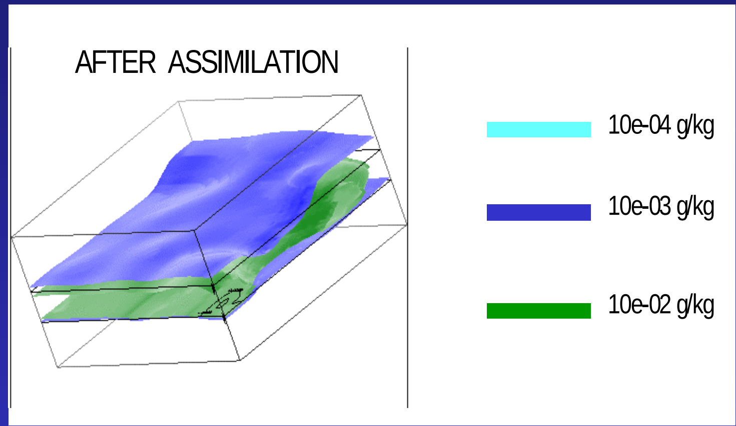
$$\frac{\partial F}{\partial x} \approx \frac{\partial H}{\partial x}$$

4DVAR cloud study results

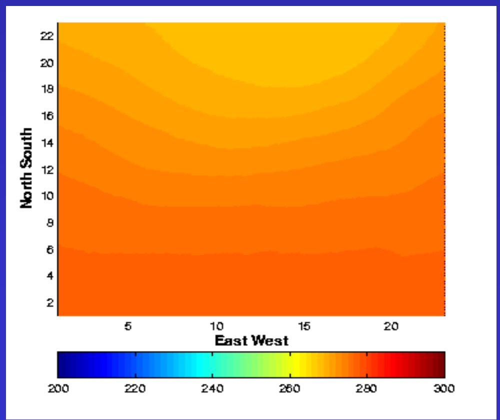


Model
3D
cloud





2D
Tb



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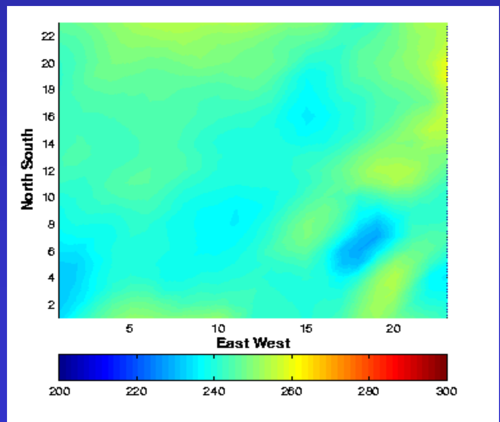

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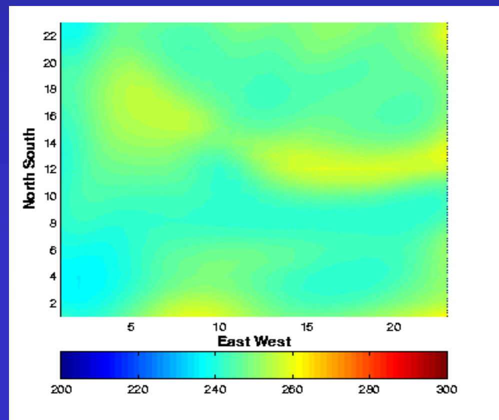


prior

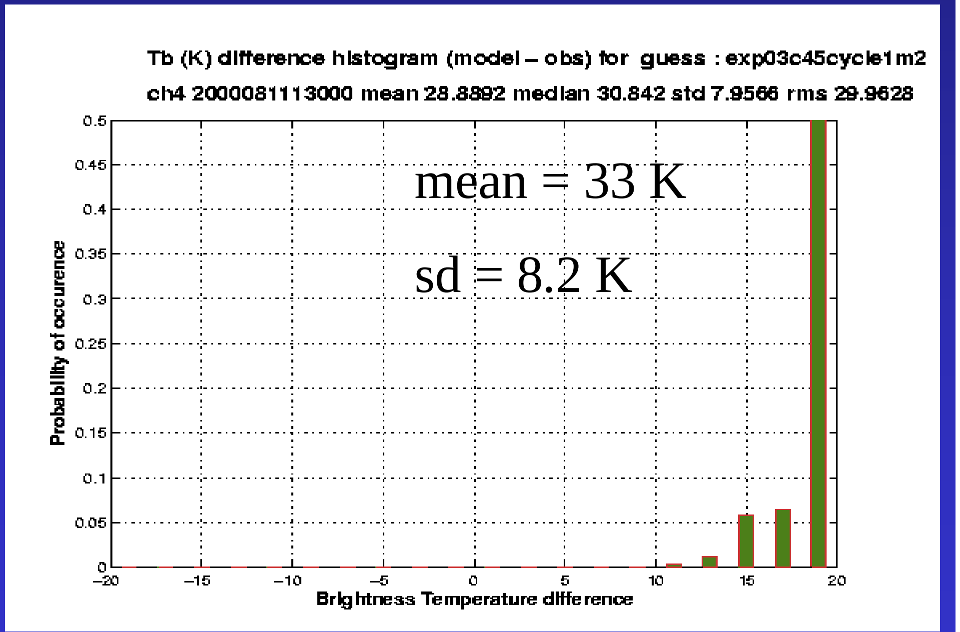
Observations
Sequence every 15 min

posterior
End time shown

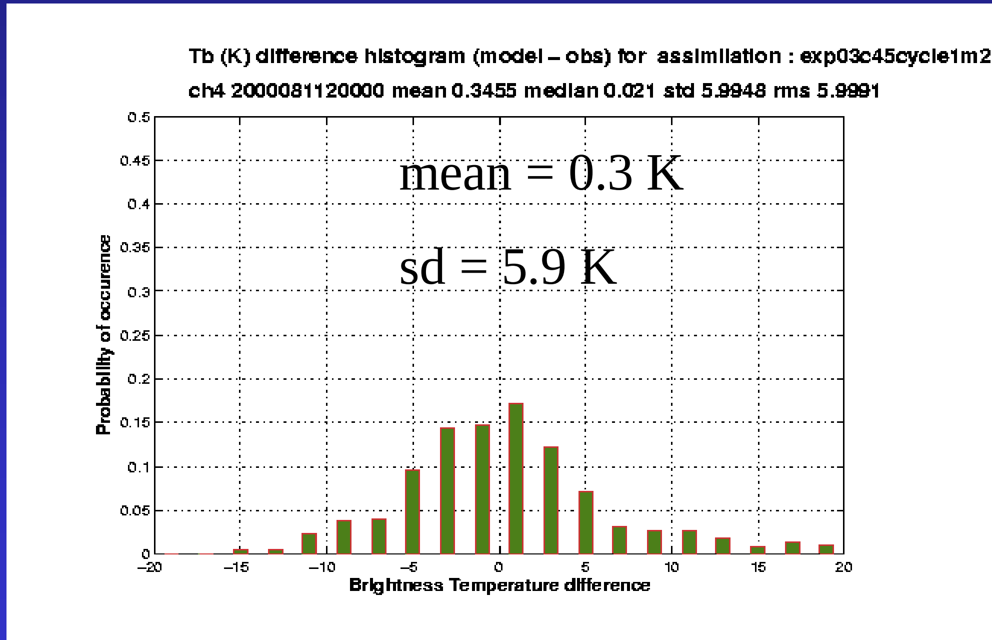
Skill of the estimate in 4D cloud study in the observation space

Brightness Temperature errors in $10.7\,\mu m$

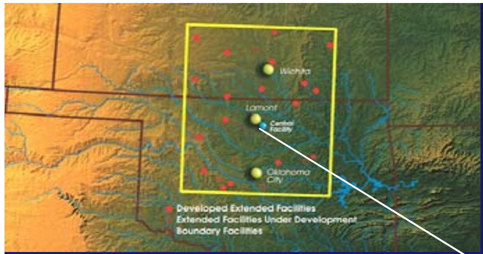
Prior errors



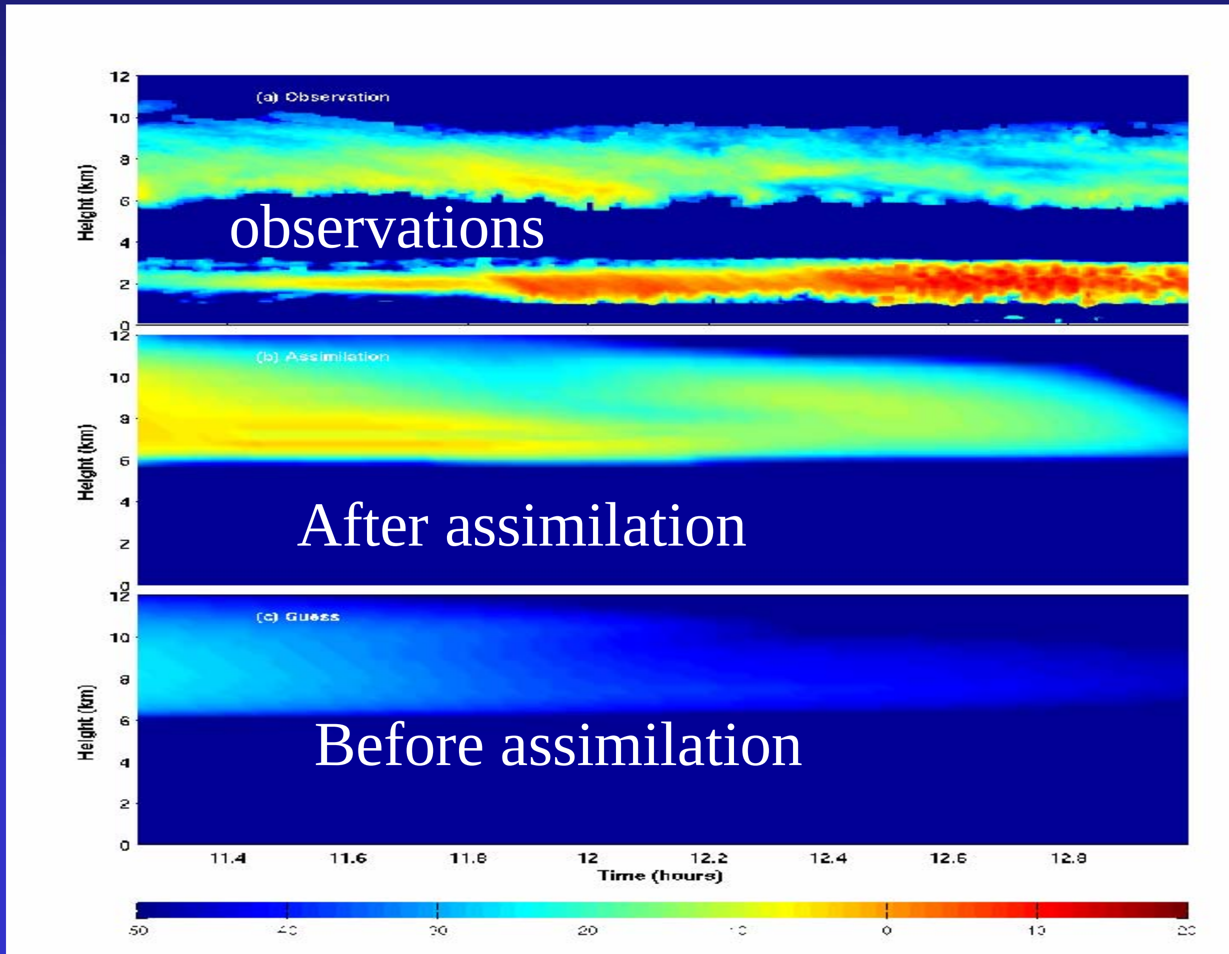
Posterior errors



Verification of the estimate in 4D cloud study against independent obs



ARM Cloud Radar reflectivity



Ice cloud

Liquid cloud

Height km

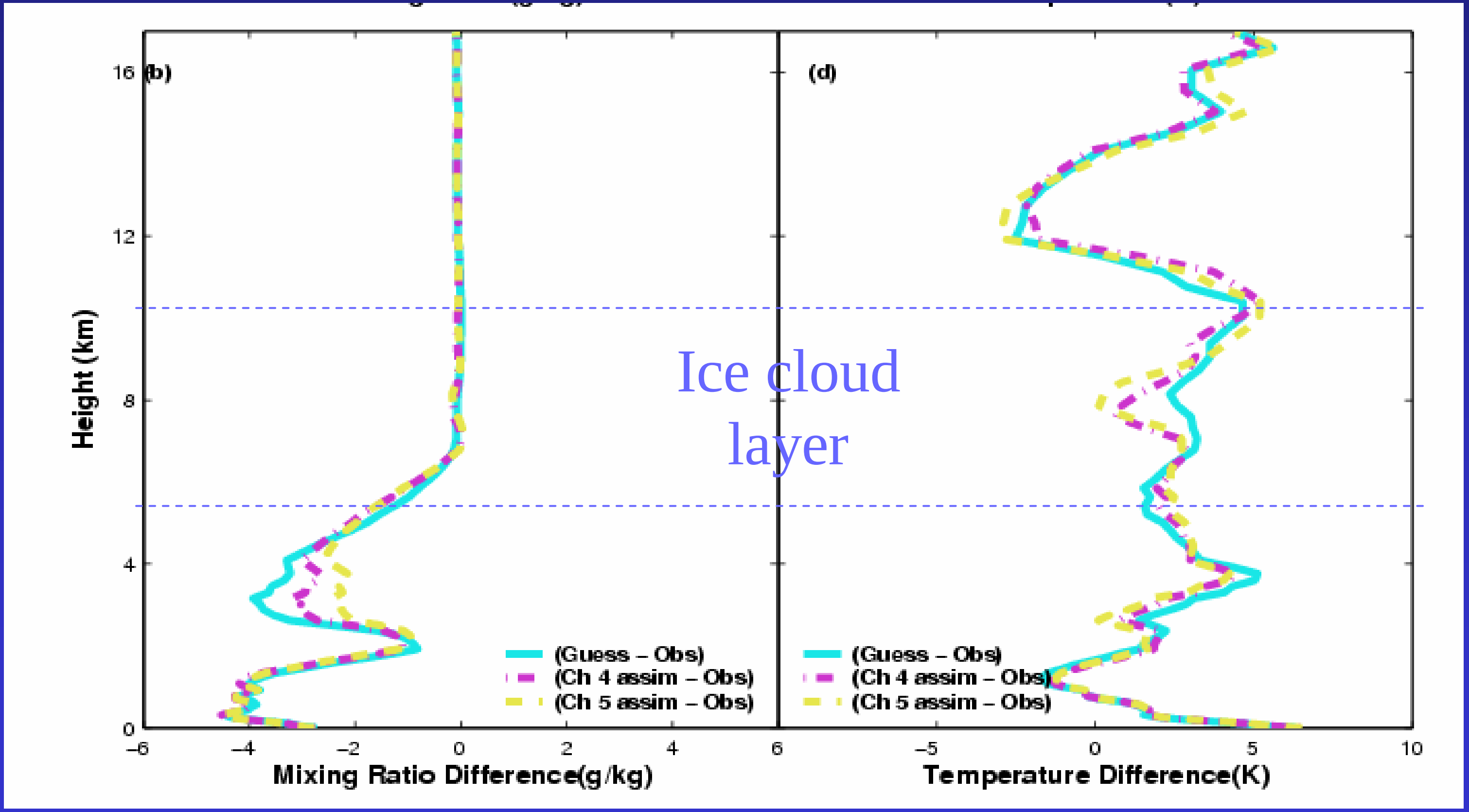
Time

1 hour

Verification of the estimate in 4D cloud study against atmospheric sounding observations

Mixing ratio error

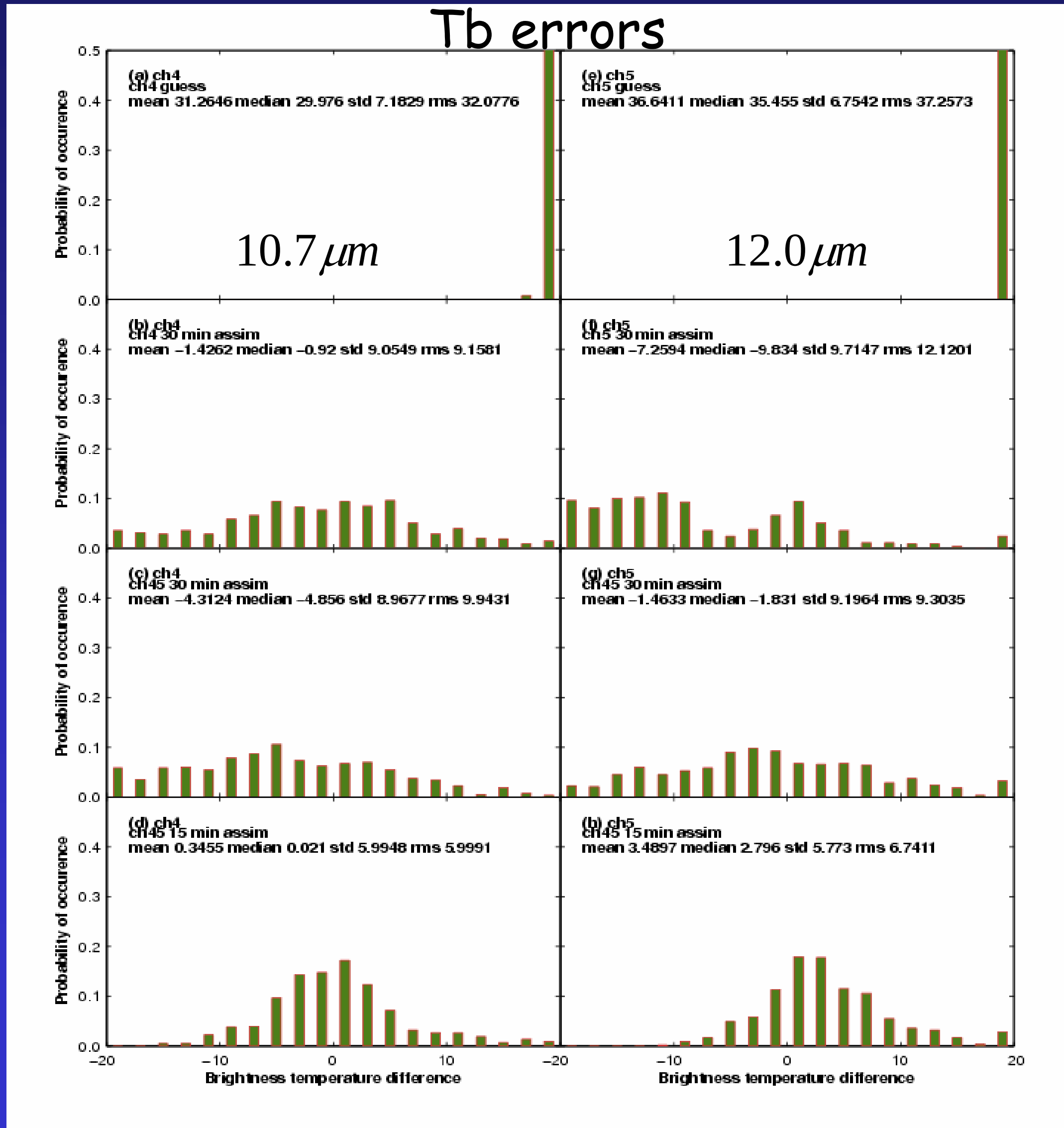
Temperature error



More observations better result

Worst

Best



Guess

Single channel assimilations, 30 min frequency

2-channel assimilation, 30 min frequency

2-channel assimilation, 15 min frequency

4D cloud study conclusions

- Modeled ice cloud significantly improved by the GOES imager IR observations
- Modeled liquid cloud not improved
  - IR observations not sensitive to liquid below ice clouds
- Modeled cloud environment slightly improved
  - Need other observations to improve it
- More frequent observations and combined channels produce better cloud estimation
- Linear model error does not work well for the cloud resolving model

EXAMPLE 2

Improving extreme precipitation forecast by advanced 4D assimilation of precipitation observations

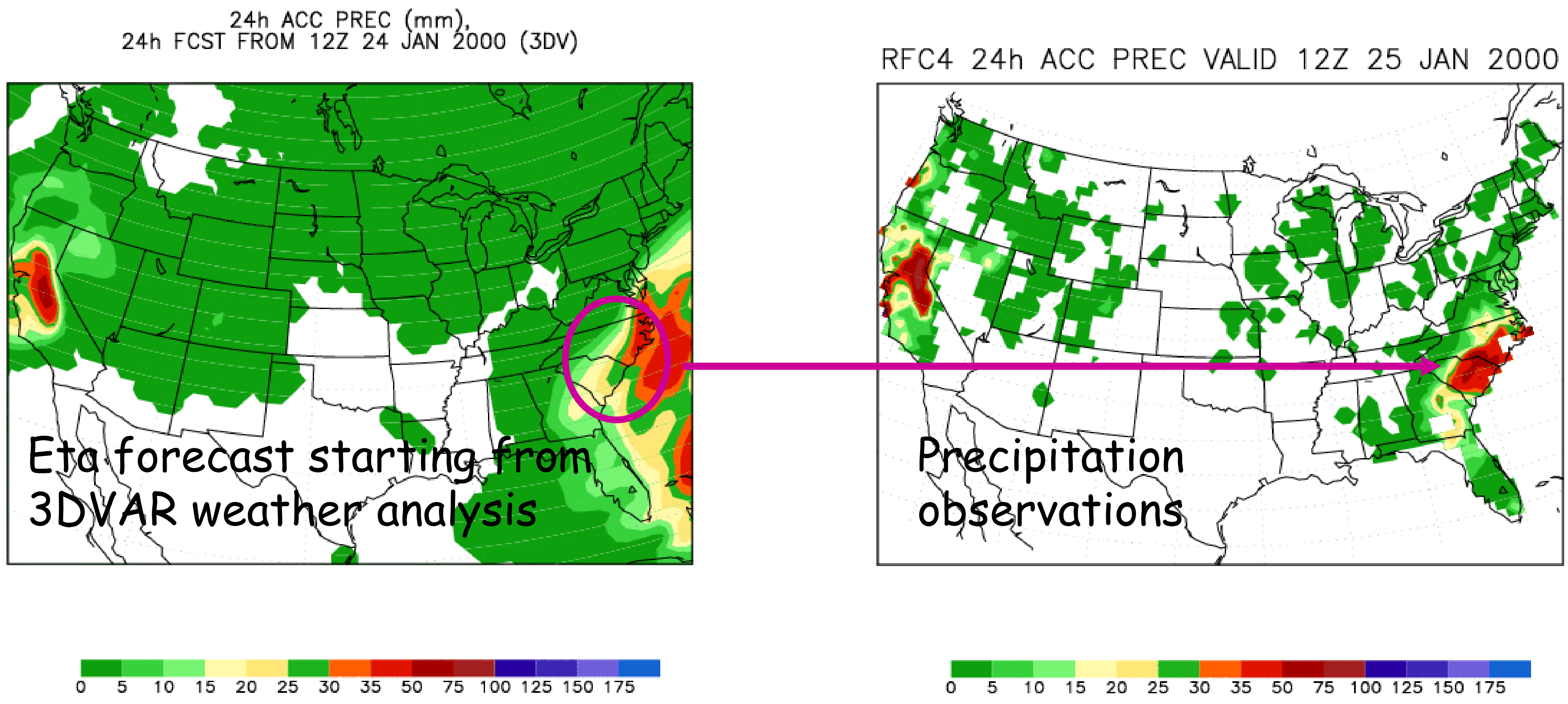
Zupanski et al. (2002, MWR)

Motivation: Accurate prediction of extreme precipitation events is critical for minimizing material damage and optimizing services

- Data assimilation technique: 4DVAR with regional national weather forecast model (Eta-model system in the USA)
- Observations : Conventional operational weather observations plus surface precipitation
- Case: US East Coast Blizzard of 2000

24-h accumulated precipitation fcst

3DVAR NCEP STAGE IV



- 3DVAR precipitation fcst incorrect, missed heavy precipitation over Carolinas

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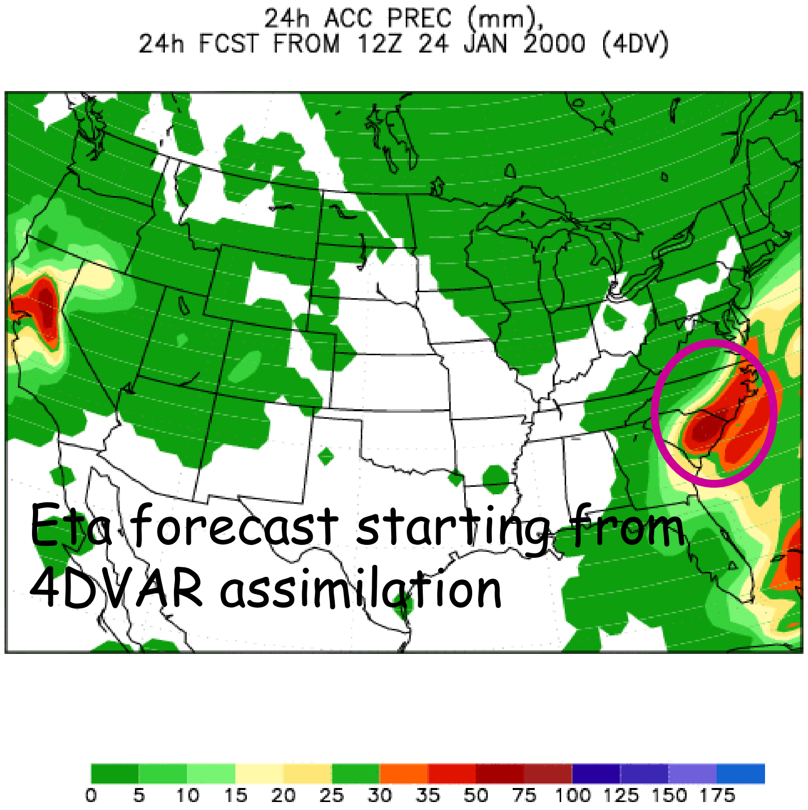
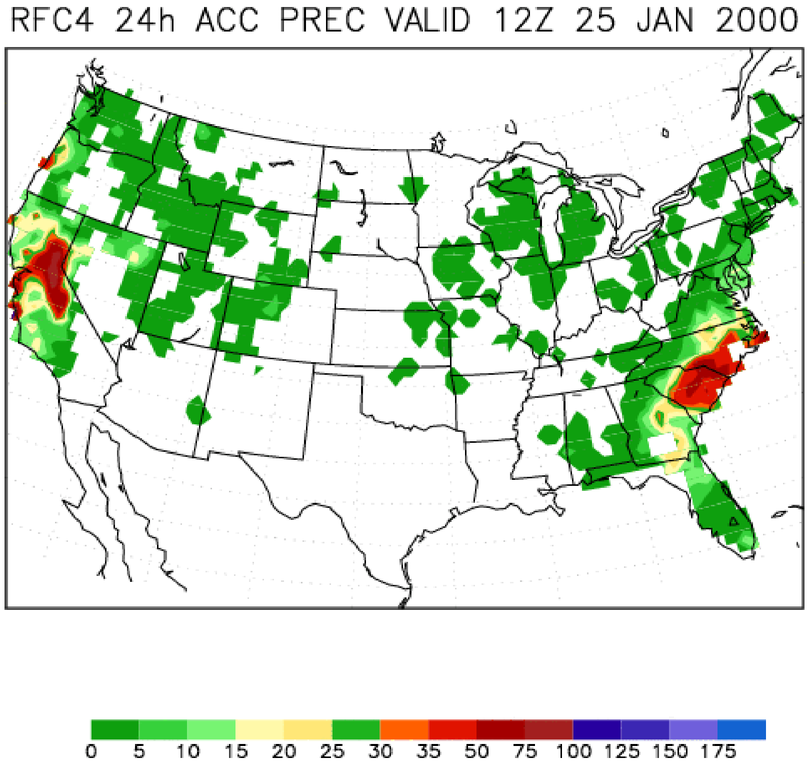
24-h accumulated precipitation fcst

4DVAR NCEP STAGE IV





- Amount and location of 4DVAR precip fcst correct

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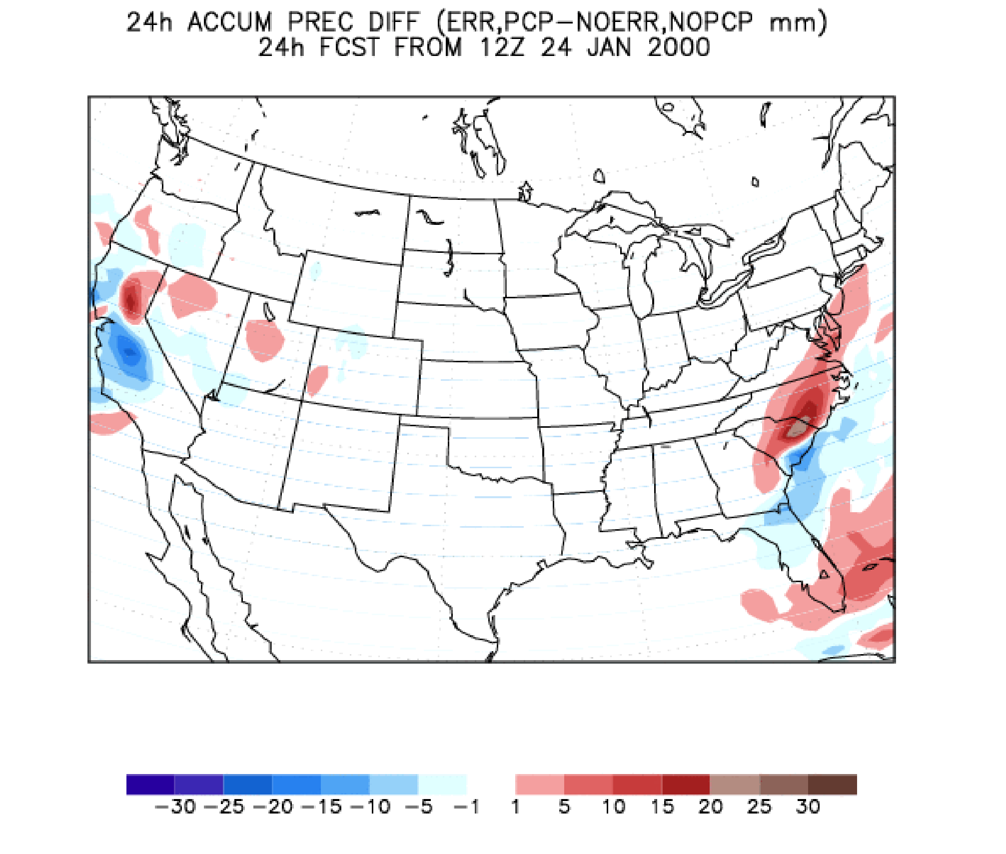
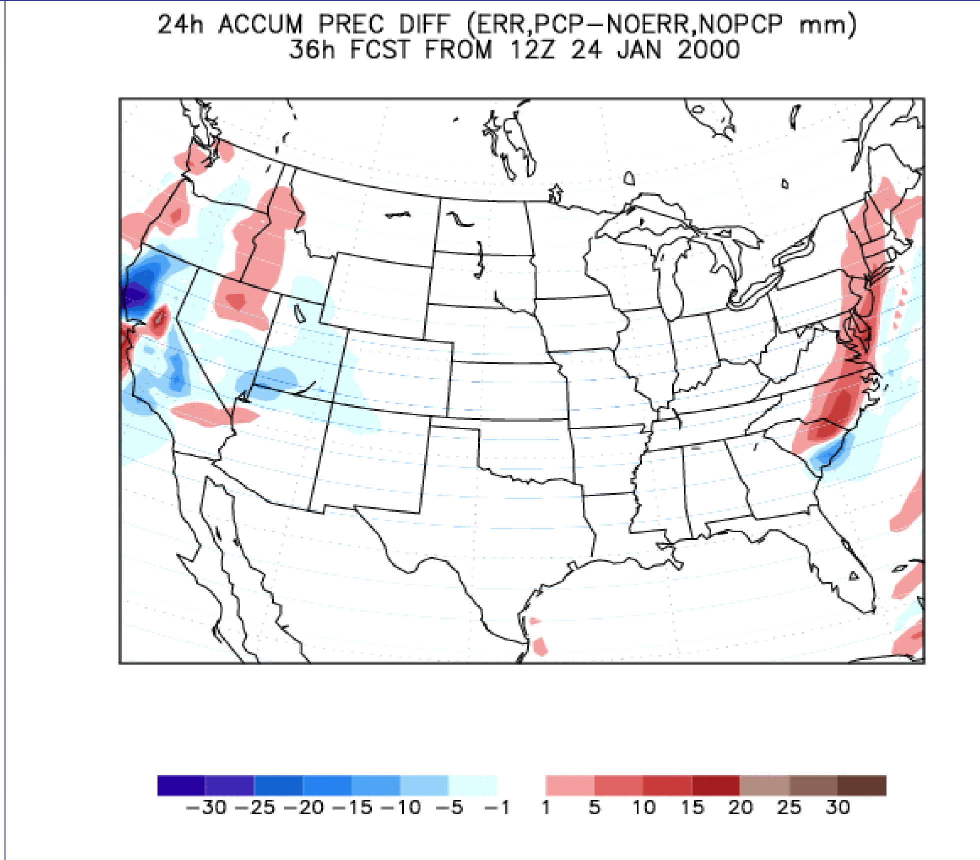
24-h accumulated precipitation difference:

4DVAR (precip + model err) - 4DVAR (basic)

24-h fcst



36-h fcst



- In 4DVAR, precipitation assimilation and model error adjustment have significant positive impact

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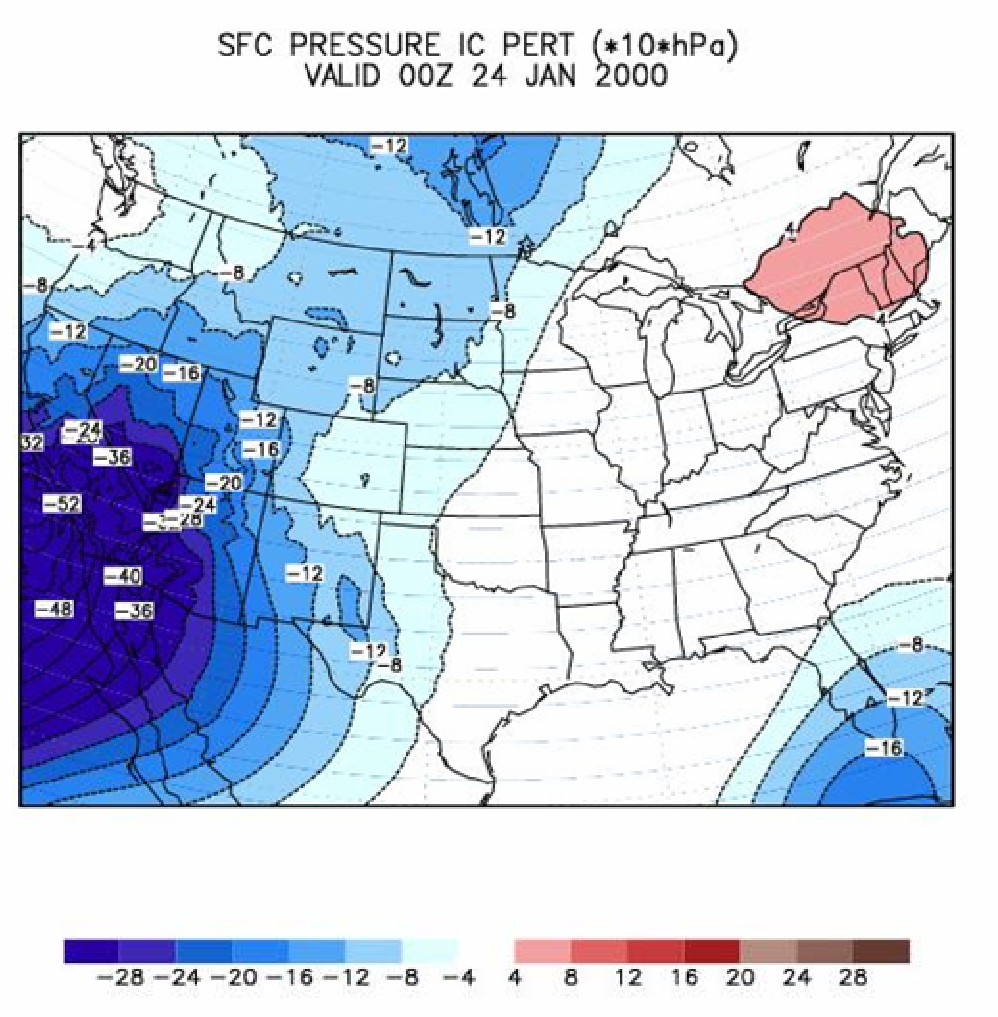
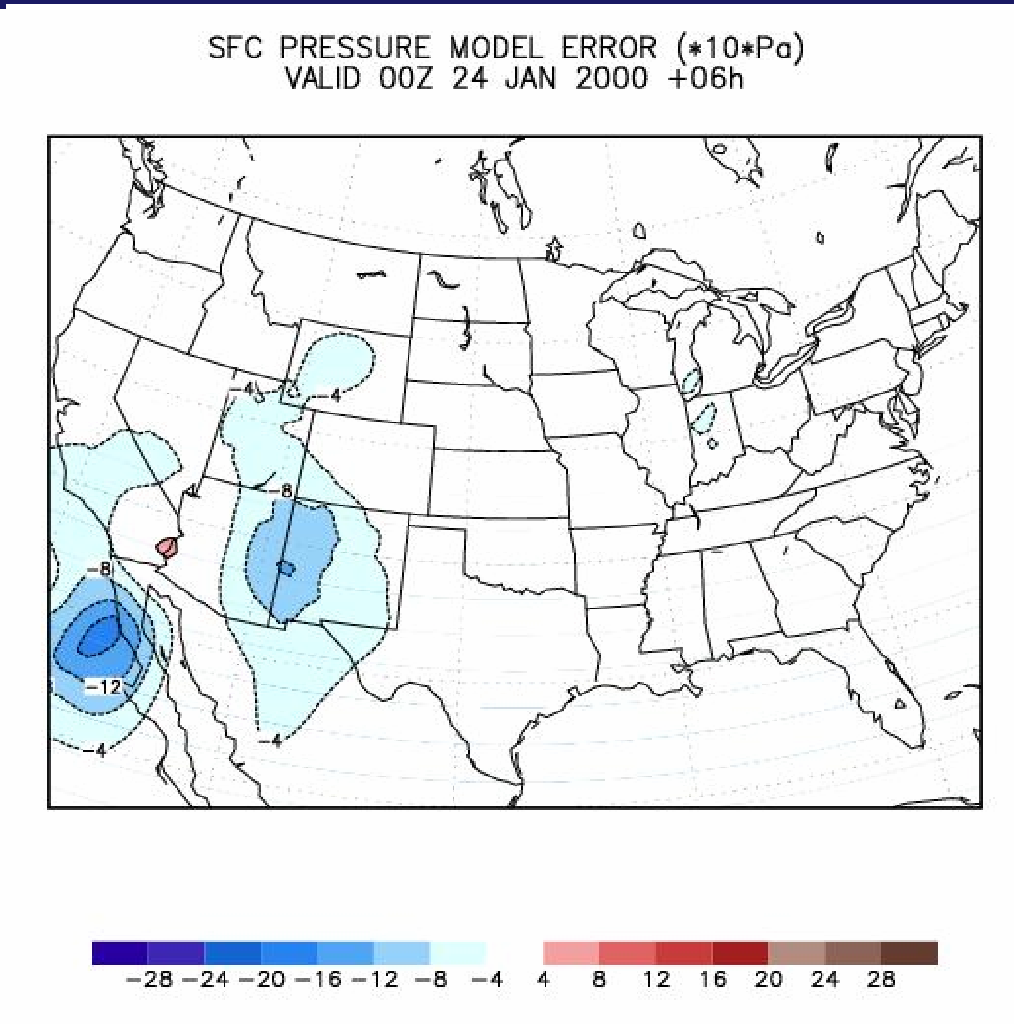
OPTIMAL IC



OPTIMAL MODEL ERROR



Initial condition and model error corrections

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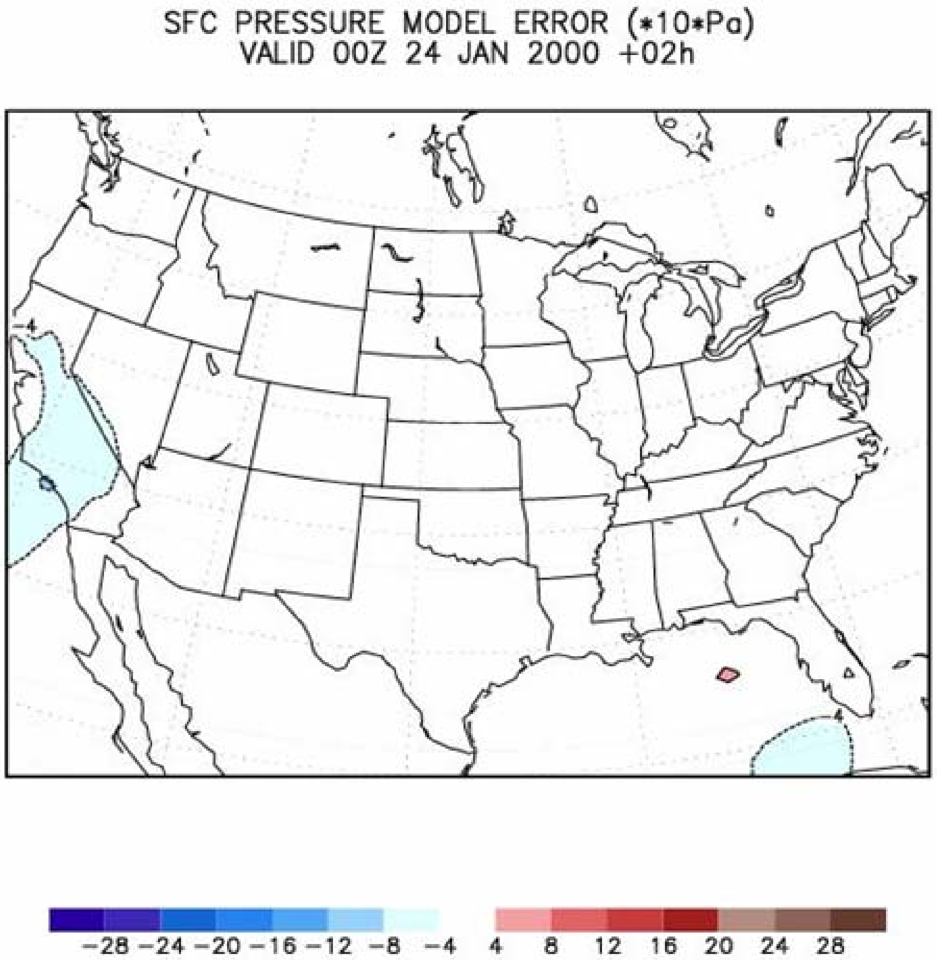
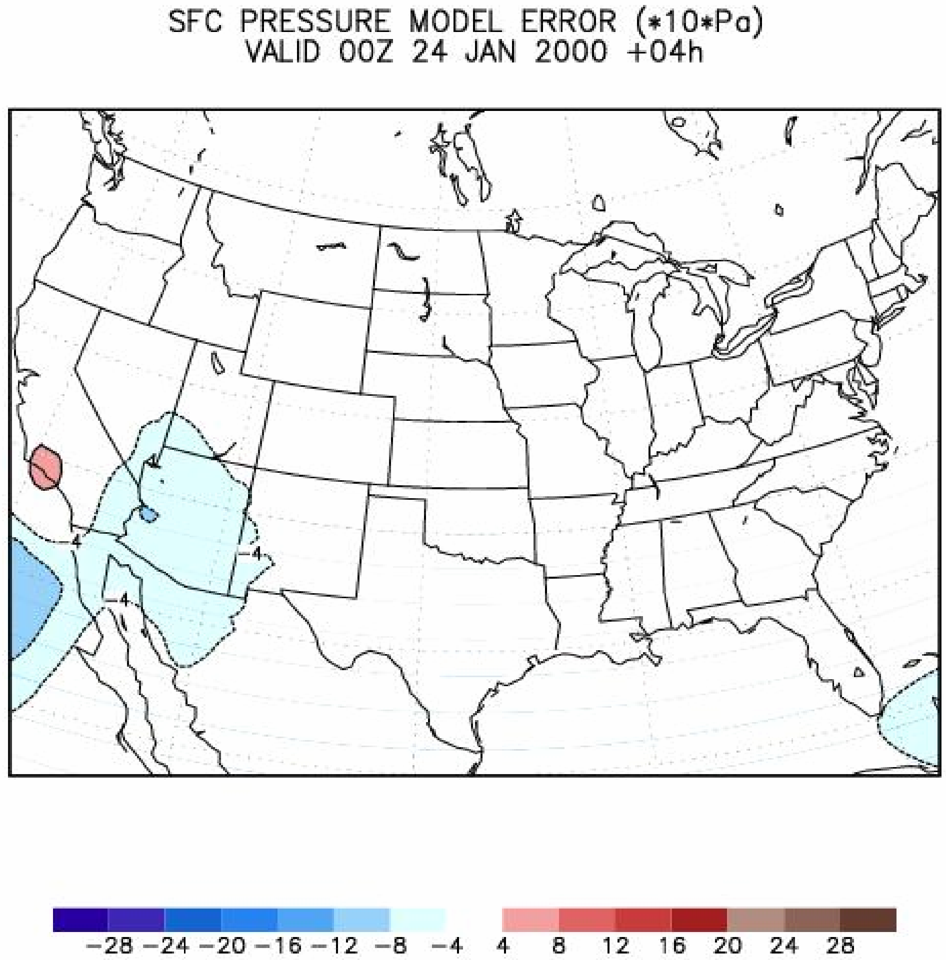
TIME EVOLUTION OF OPTIMIZED MODEL ERROR





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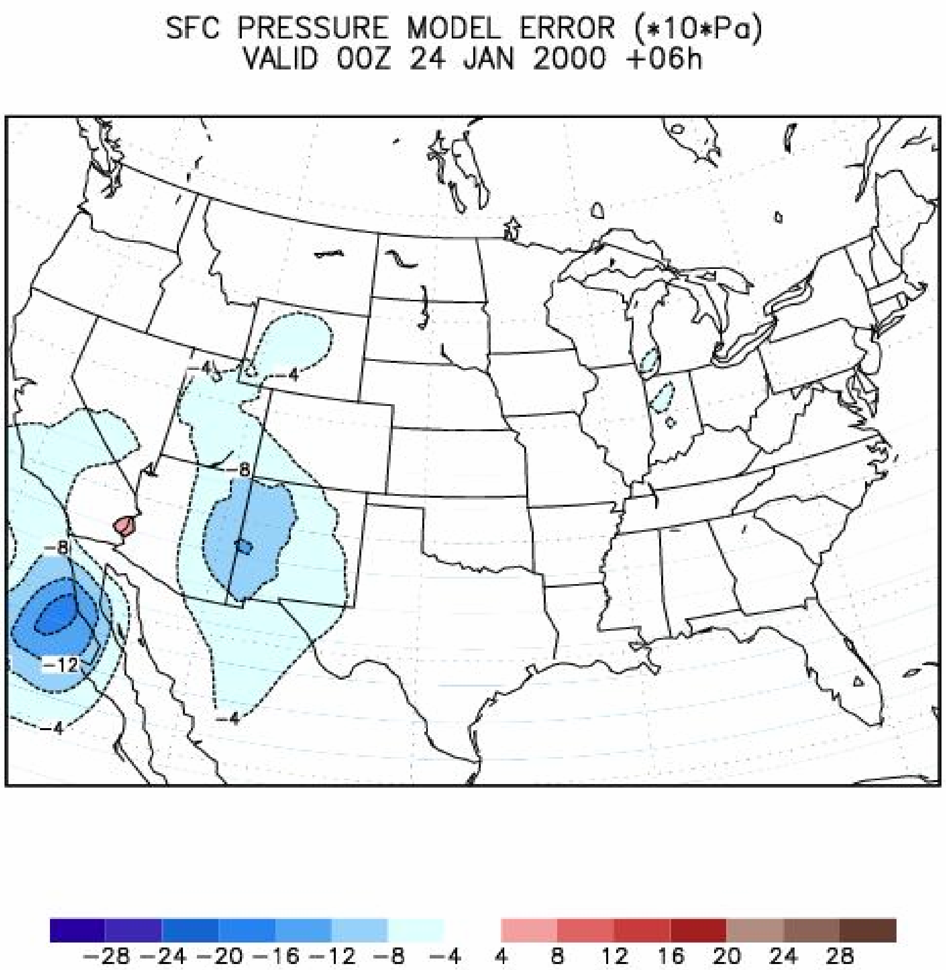
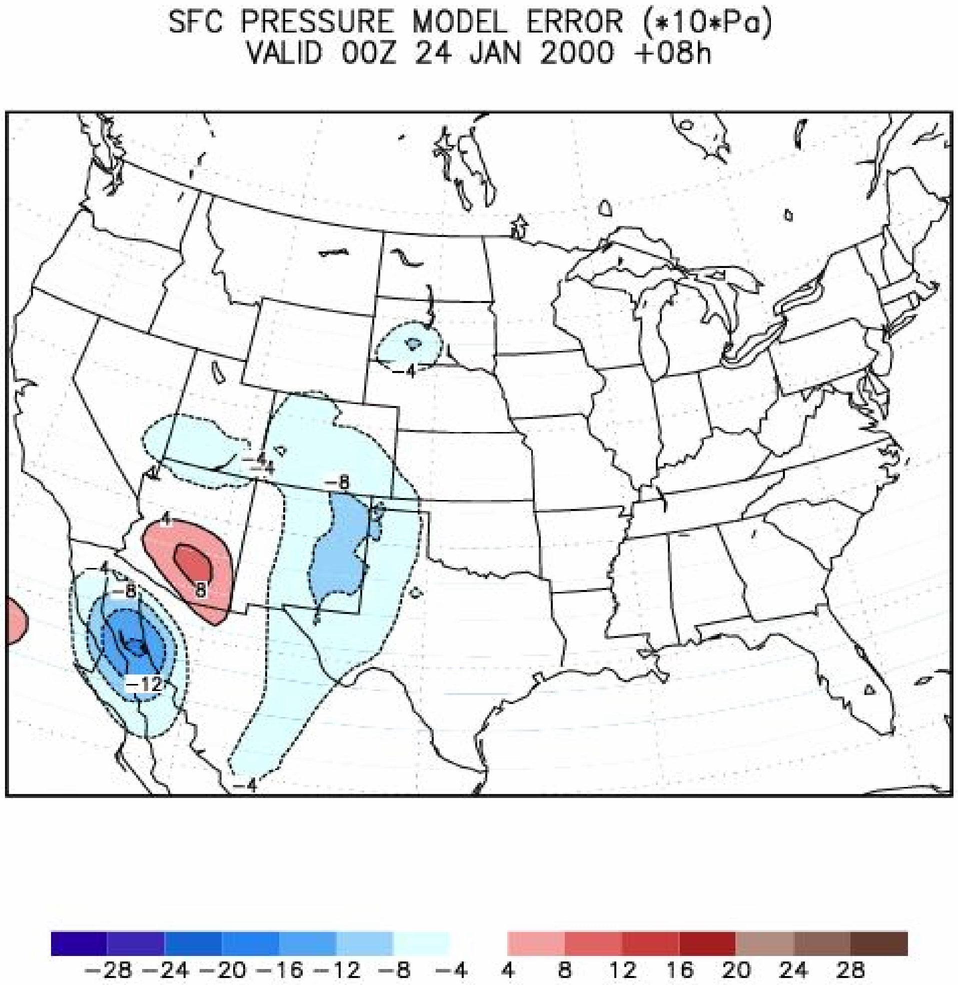
TIME EVOLUTION OF OPTIMIZED MODEL ERROR





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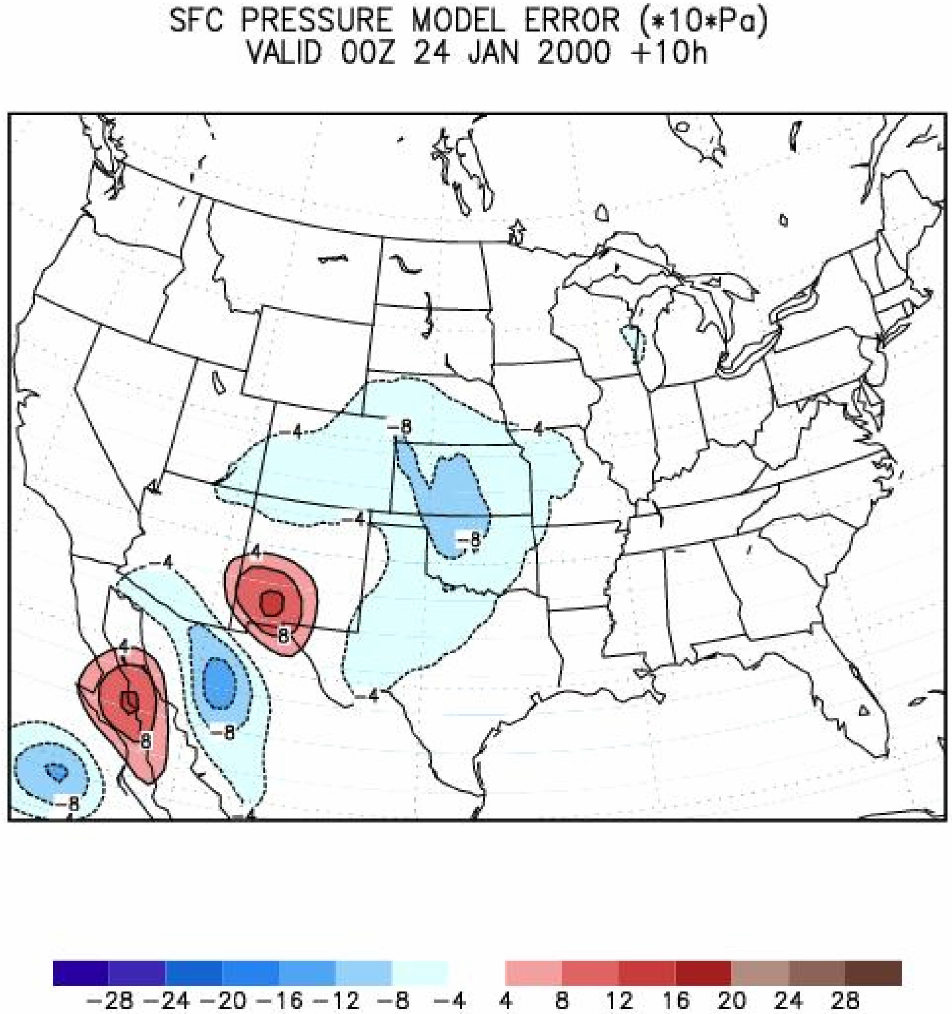
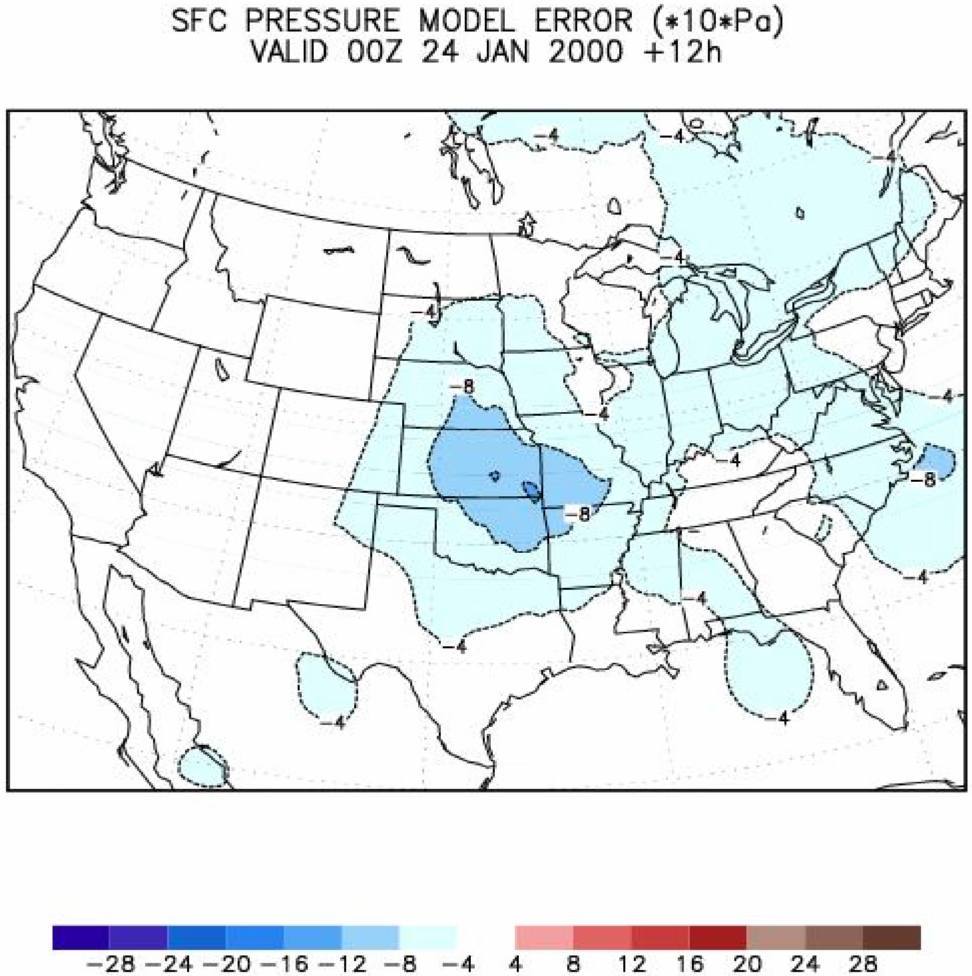
TIME EVOLUTION OF OPTIMIZED MODEL ERROR





Model error is characterized with fast propagation

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Zupanski et al (2002) conclusions

- Assimilation of precipitation significantly improves the analysis and prediction of precipitation
- Including of the model error control parameter has positive impact on the assimilation

EXAMPLE 3

Convective scale short term prediction model initialization by doppler radar observations

Snyder and Zhang (2003. MWR)

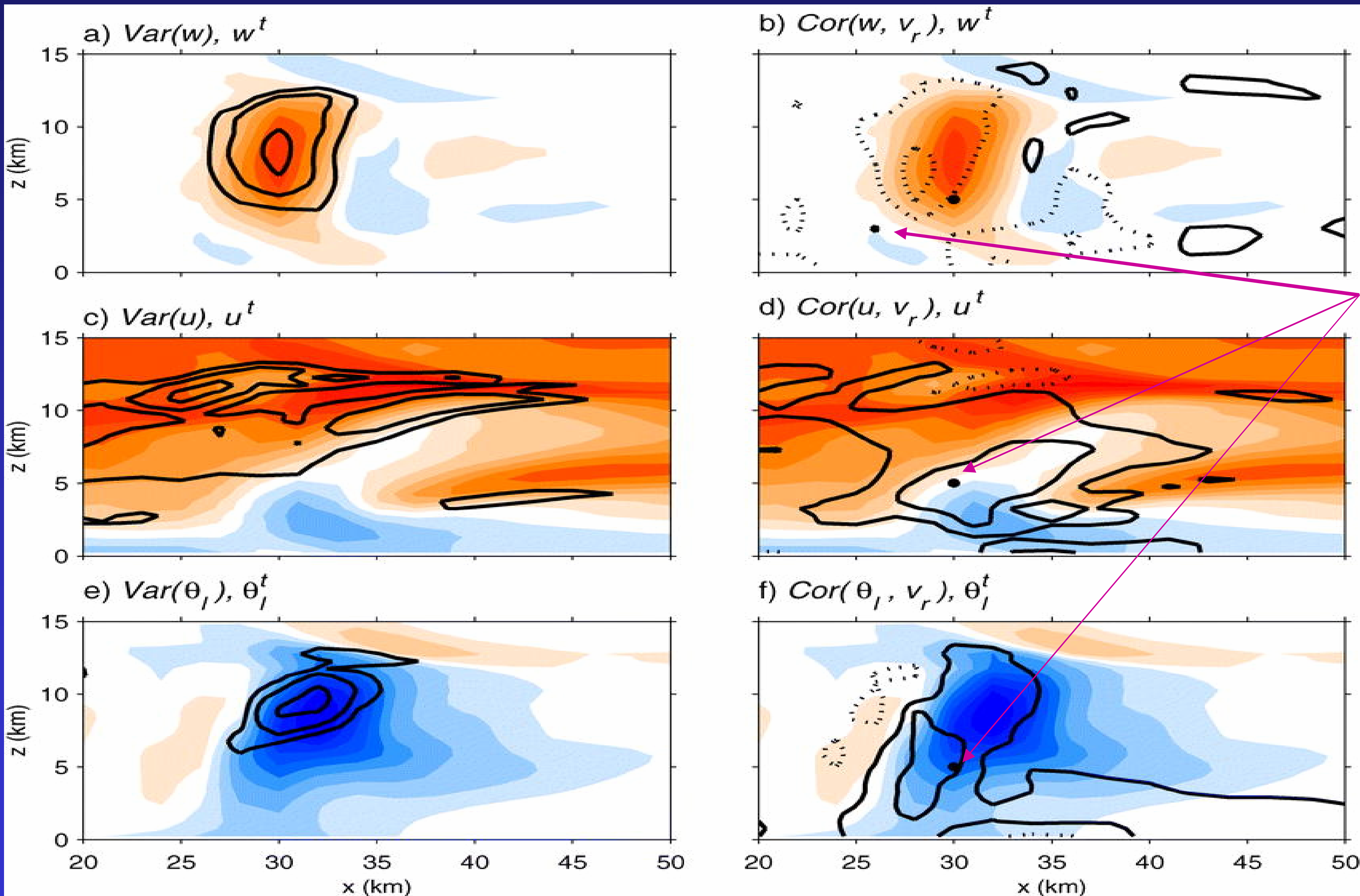
Motivation: Improved analysis of convective scale weather is desirable to extend the accuracy of short term severe weather warning

- Data assimilation technique: Ensemble KF with convection resolving model (NCAR, USA)
- Observations : Doppler radar radial velocity
- Case: Isolated super-cell thunderstorm

Experiment design

- Synthetic observations of doppler radar radial velocity
- Reference simulation initialized from single atmospheric sounding
- 50 ensemble members
- 80 min simulation with 2 km grid resolution
- Perfect model assumption

Ensemble models correlations between observed and unobserved quantities



Location of observed radial velocity

Snyder and Zhang (2003) conclusions

- EnKF can be applied to convective scale initialization using high temporal resolution radar data and skilled model
- Model error should be included

Summary

- The data assimilation is powerful approach to improving the accuracy of modeled and predicted weather at all scales
- The data assimilation techniques (4DVAR and EnKF) are computationally expensive but the benefits should outweigh the cost
- Research challenges in the data assimilation:
  - Treatment of non_Gaussian probability distributions
    - Important when nonlinear processes are dominant
  - Model dependent model error formulation
    - Convective and cloud scale models need nonlinear model error
  - Optimal use of large volume of satellite measurements
    - Information content optimization