Model error representation in ensemble convection-permitting forecasts and ensemble data assimilation

Glen Romine NCAR (MMM/IMAGe)

ECMWF Model Uncertainty Workshop
Reading, UK, 04/13/2016

NCAR Collaborators: Craig Schwartz, Ryan Sobash, Kate Fossell, Judith Berner

Core motivation: hazardous weather prediction

Severe convection with the right combination of:

- Moisture
- Instability
- A lift mechanism
- Sufficient shear

Key forecast challenges to address:

What is the probability that convection will occur at a given location?

How intense might convection be?

What convective modes are favored (primary hazards)?

NCAR

Ensemble forecast system framework

Forecast system design components:

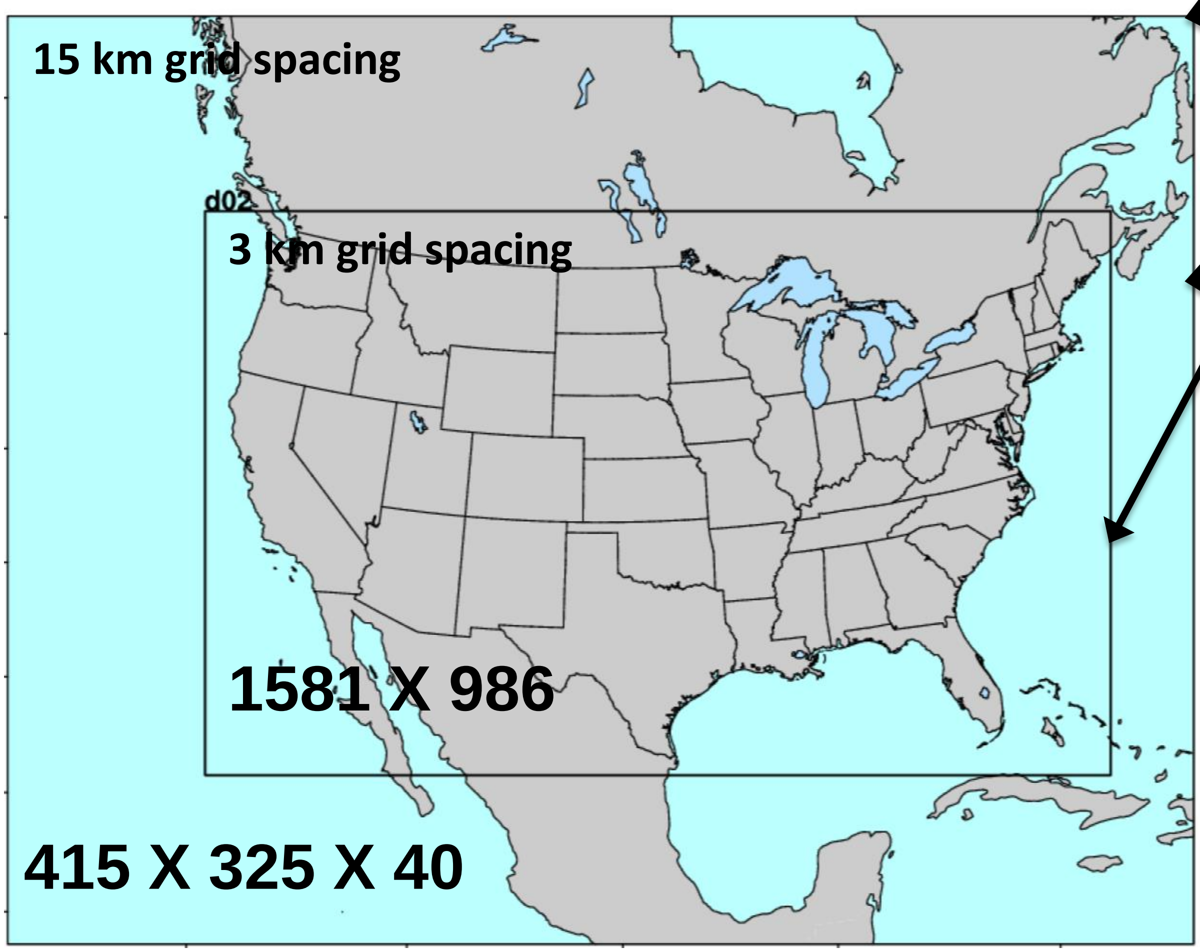
- Ensemble – want probabilistic, not deterministic predictions
- High-resolution for convective mode and intensity (convection-allowing (CAM) horizontal grid spacing)
- Computational constraint - **regional model** (e.g., WRF)
- Ensemble data assimilation for initial conditions (e.g., DART)

Regional ensemble forecast system components:

- Initial condition uncertainty (e.g., ensemble DA)
- Surface and lateral boundary condition uncertainty
- Model error representation – **CAMs are notoriously under dispersive!**

Example: NCAR Real-time ensemble

GFS + perturbations



GFS + perturbations

GFS + perturbations

GFS + perturbations

Analysis domain
(50 members)
EAKF

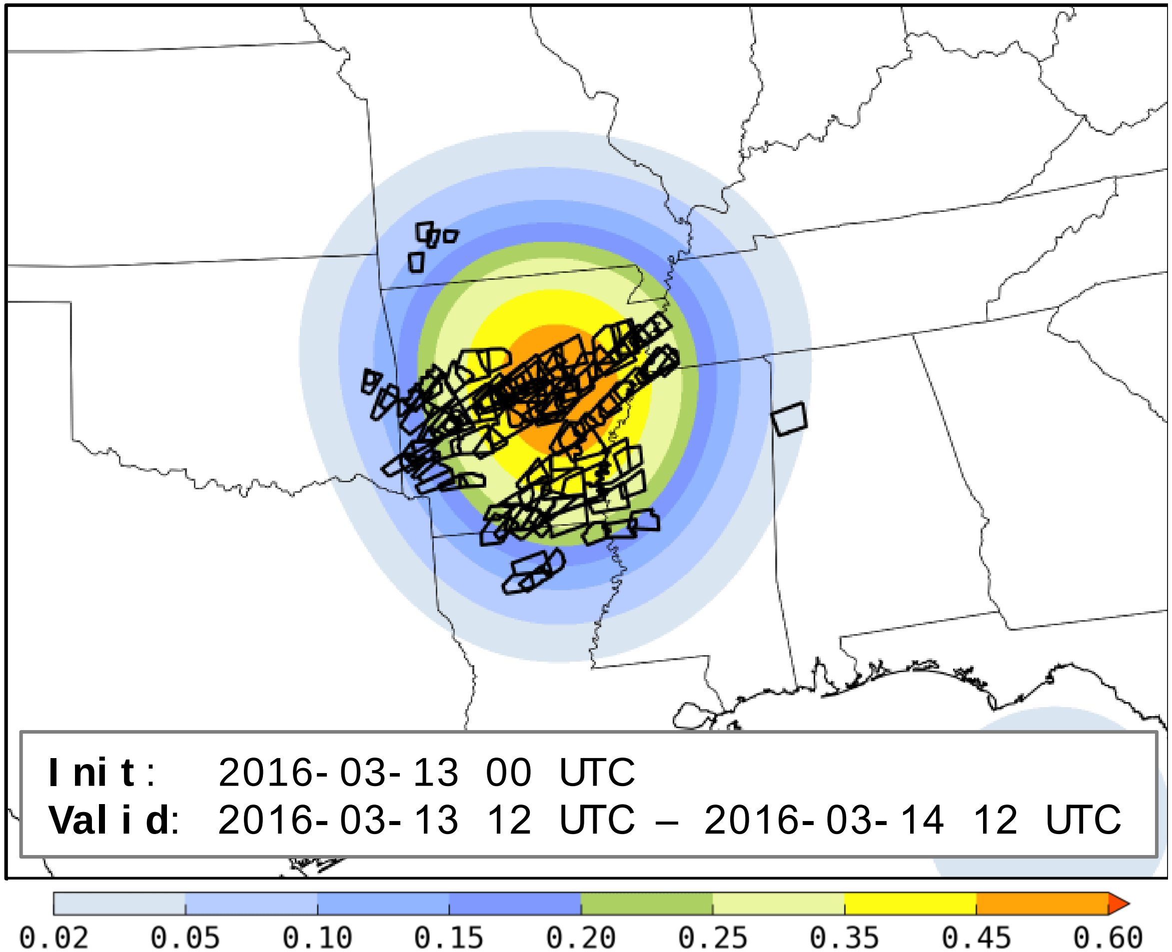
Forecast domains
(10 members)

ensemble.ucar.edu

Lower boundary: free forecast land surface, fixed sea state

NCAR ensemble – hazard prediction sample

Day 1 probability of UH > 75 m^2/s^2 w/ NWS warnings



Probability of simulated supercell thunderstorms (fill) overlain with issued severe weather warnings during the valid prediction period

See Sobash et al. (2016) for more on this effort

NCAR ensemble – skill/reliability for precipitation

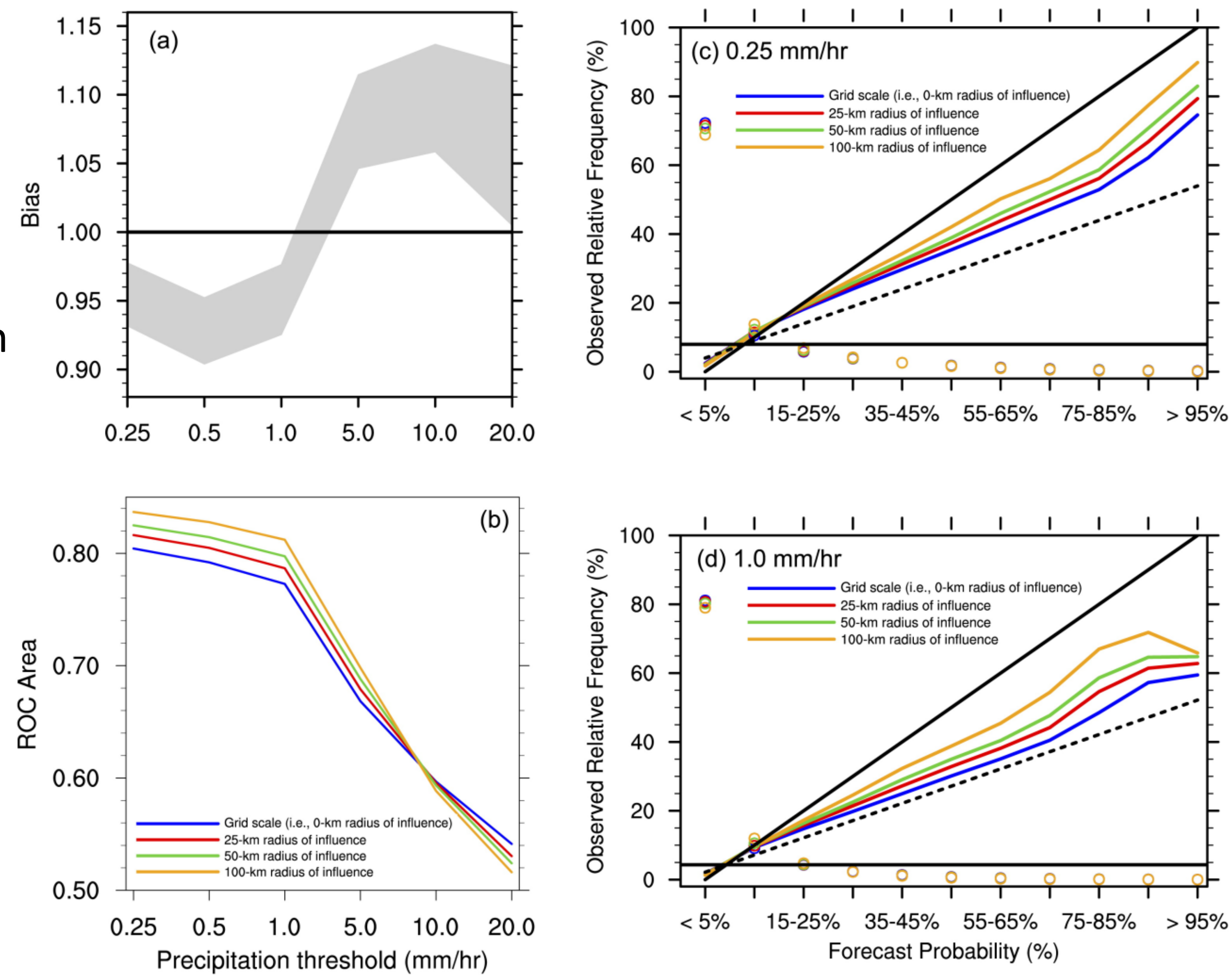
Skillful across range of rainfall intensity, more skillful with larger neighborhood for verification

Modest bias at all intensities

Underdispersive*, less so
For larger neighborhoods

* IC/BC perturbations only
* No obs error assumption

Model error treatment?



Schwartz et al. (2015)

Model error representation in CAM ensembles

None

Rely on lateral boundary perturbations and initial condition diversity

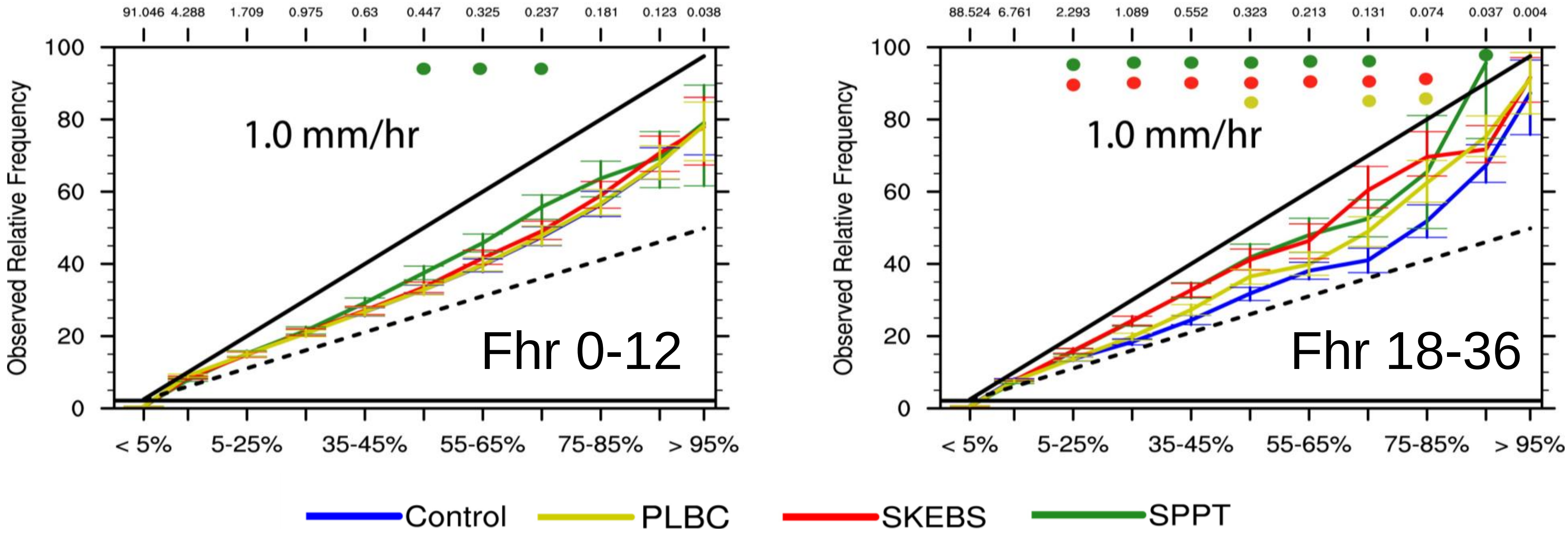
Multi-model/multi-physics/multi-parameter

- Uncertain representations of physical processes
- Model dynamics/assumptions drive model climate
- Ensemble members may have varying skill and biases
- May be challenging to post-process (e.g. grids, variables, state size)

Stochastic methods

- Random model error process (ideally)
- Single model and physics climate
- Options available in WRF-ARW:
  1) Stochastic Kinetic Energy Backscatter Scheme (**SKEBS**)
  2) Stochastically Perturbed Parameterization Tendencies (**SPPT**)

Ensemble reliability – precipitation

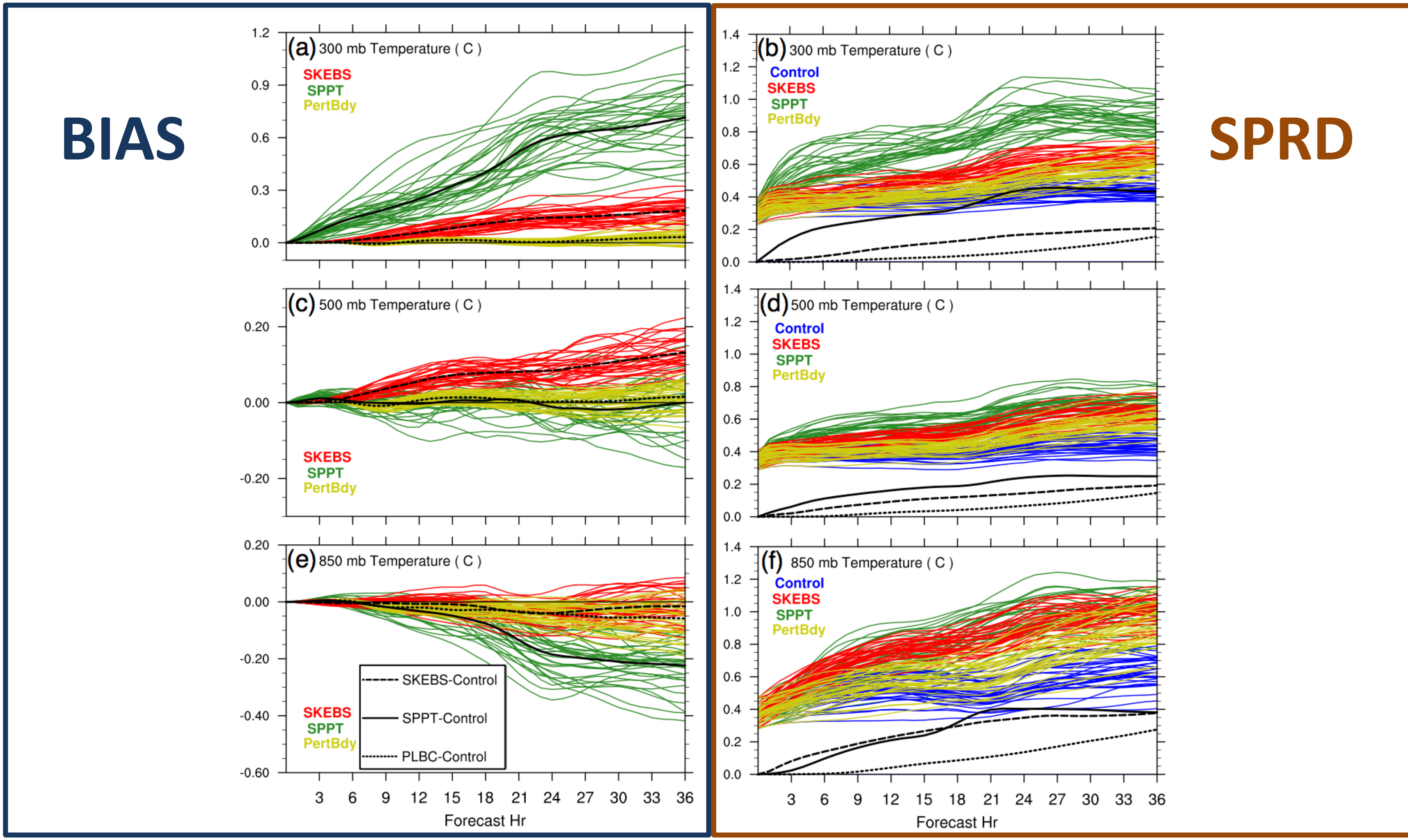


Attributes diagrams @ 1 mm h^{-1} threshold

Overconfident predictions of precipitation (no observation error)

Stochastic methods can improve reliability in longer range storm-scale forecasts, but little impact on short-range (< 12 h) prediction

Forecast bias and spread time series - temperature

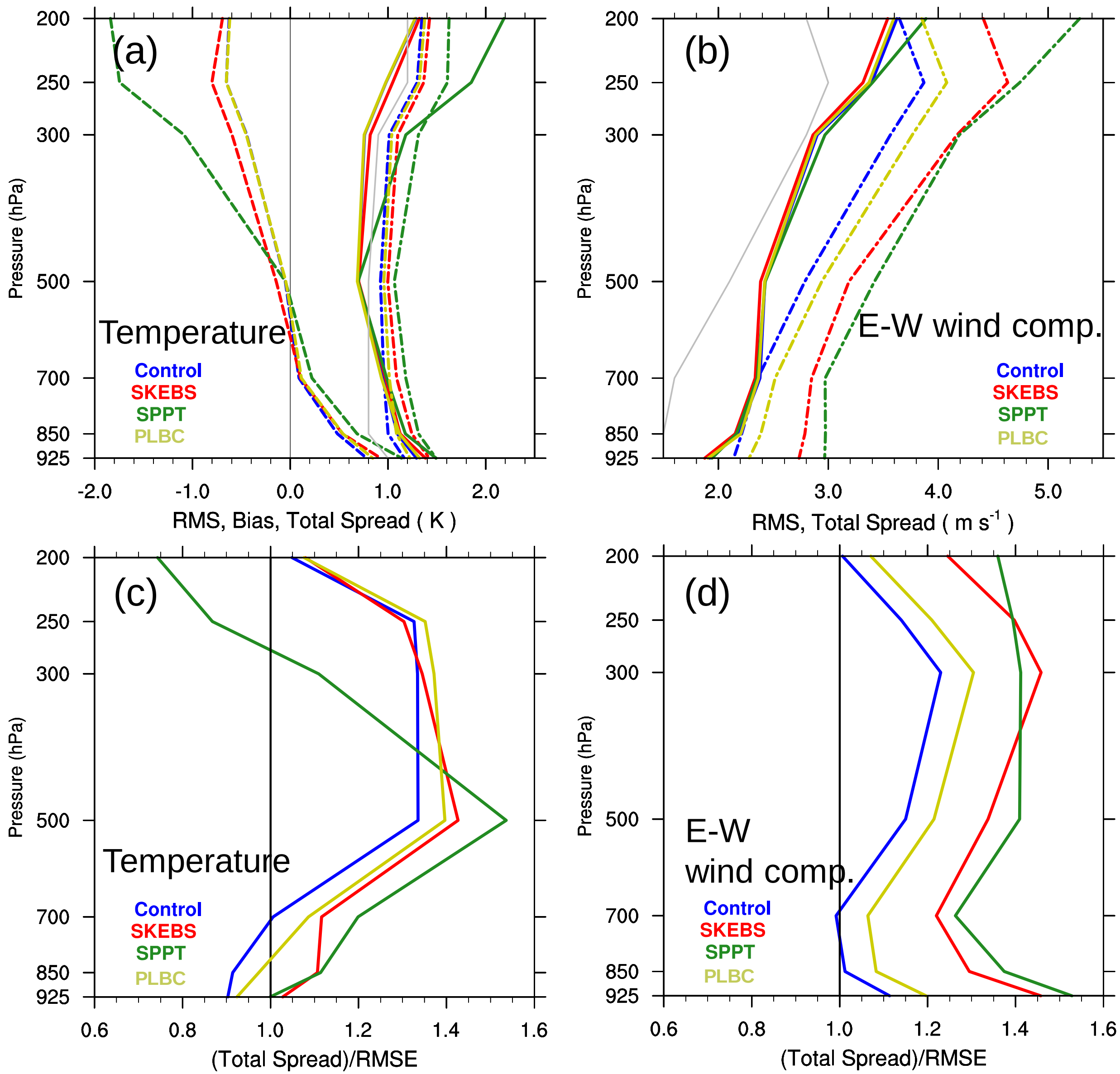


Bias drift relative to Control forecast

SPPT – largest bias drift, but also largest spread

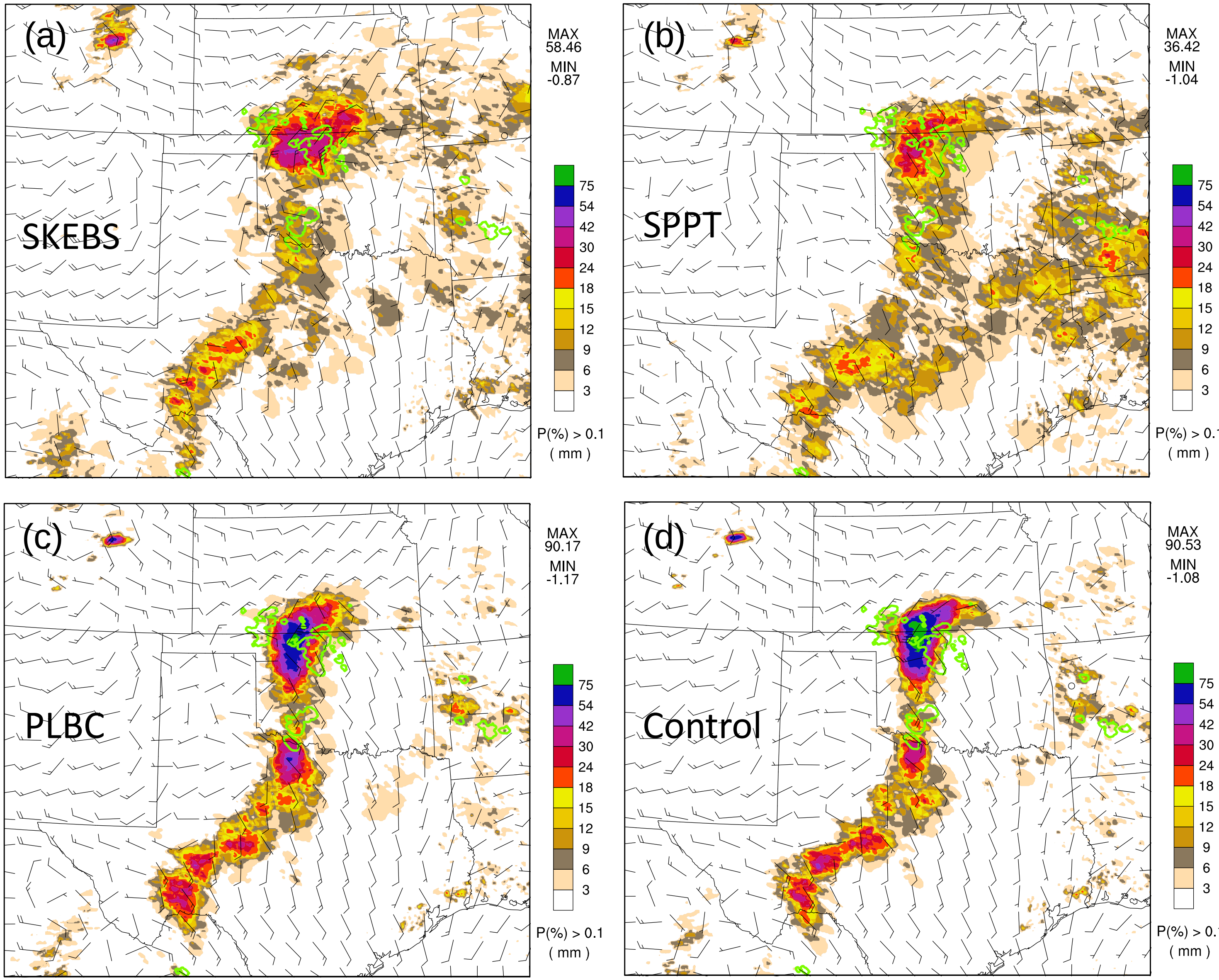
NCAR

Forecast verification against rawinsondes



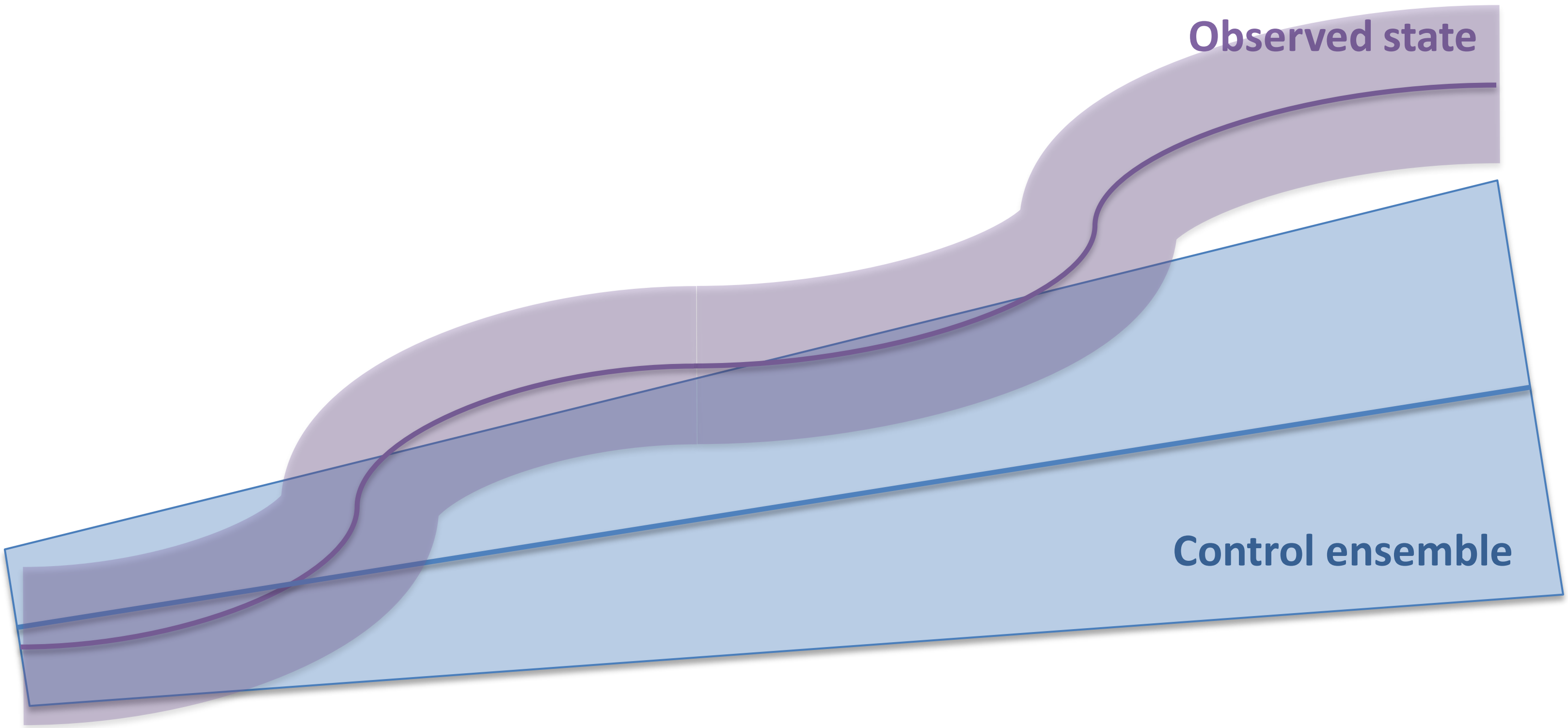
Verification against 24 h forecasts

Practical reliability for precipitation forecasts



NCAR

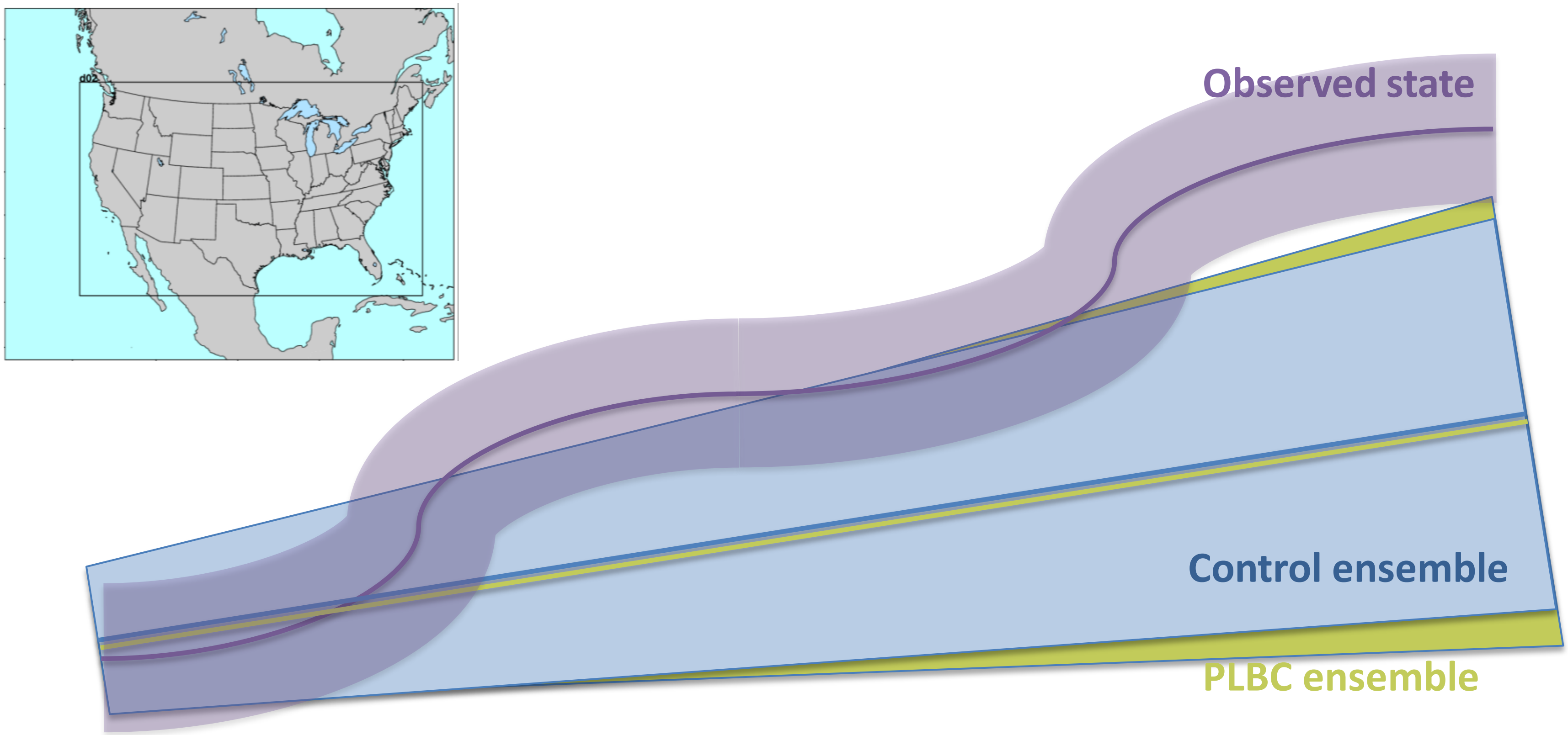
Cartoon of NCAR ensemble perturbation methods



Control ensemble:
Estimates true evolution of the atmosphere
Lacks sufficient dispersion to capture the observed evolution after short integration

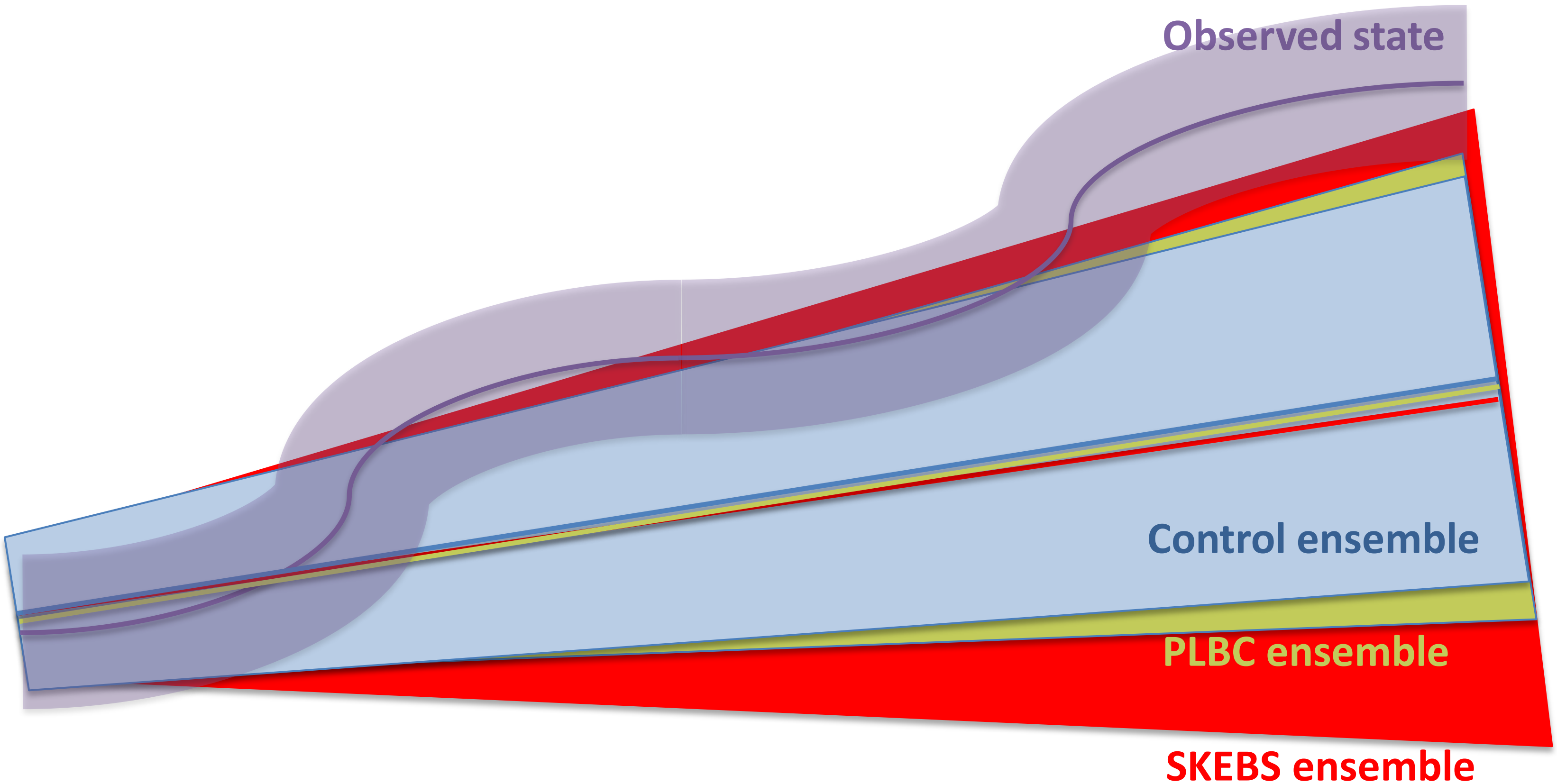
Select options:
Multi-XXX, calibration, perturbed boundaries, stochastic methods

Cartoon of NCAR ensemble perturbation methods



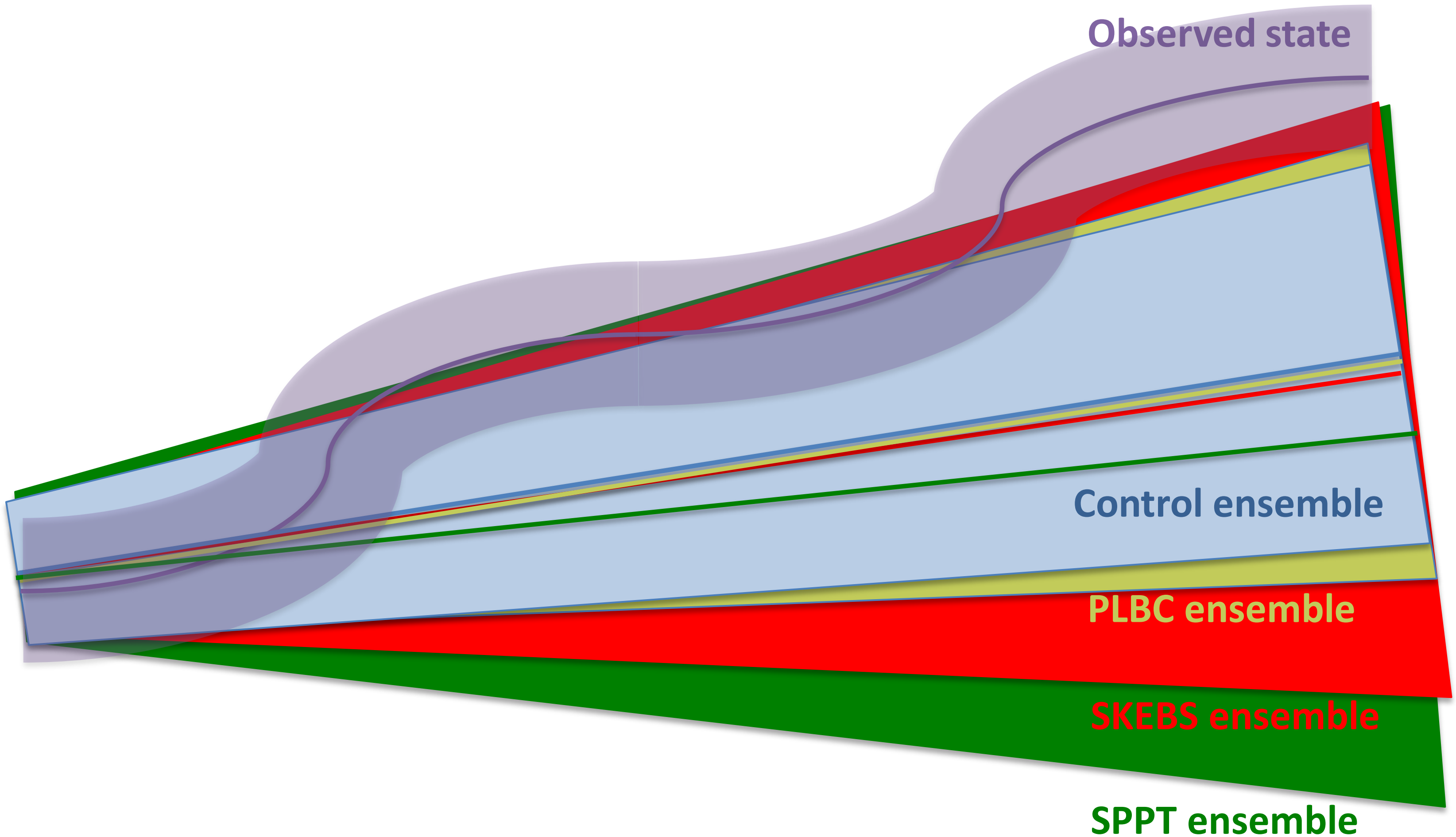
For the NCAR ensemble, perturbing the lateral boundary condition improves spread somewhat, but late in the forecast. Ensemble mean is about the same. Note forecast area is far removed from true lateral boundaries.

Cartoon of NCAR ensemble perturbation methods



SKEBS leads to greater dispersion, beginning earlier in the forecast, with nearly the same ensemble mean as the control and perturbed boundary ensemble.

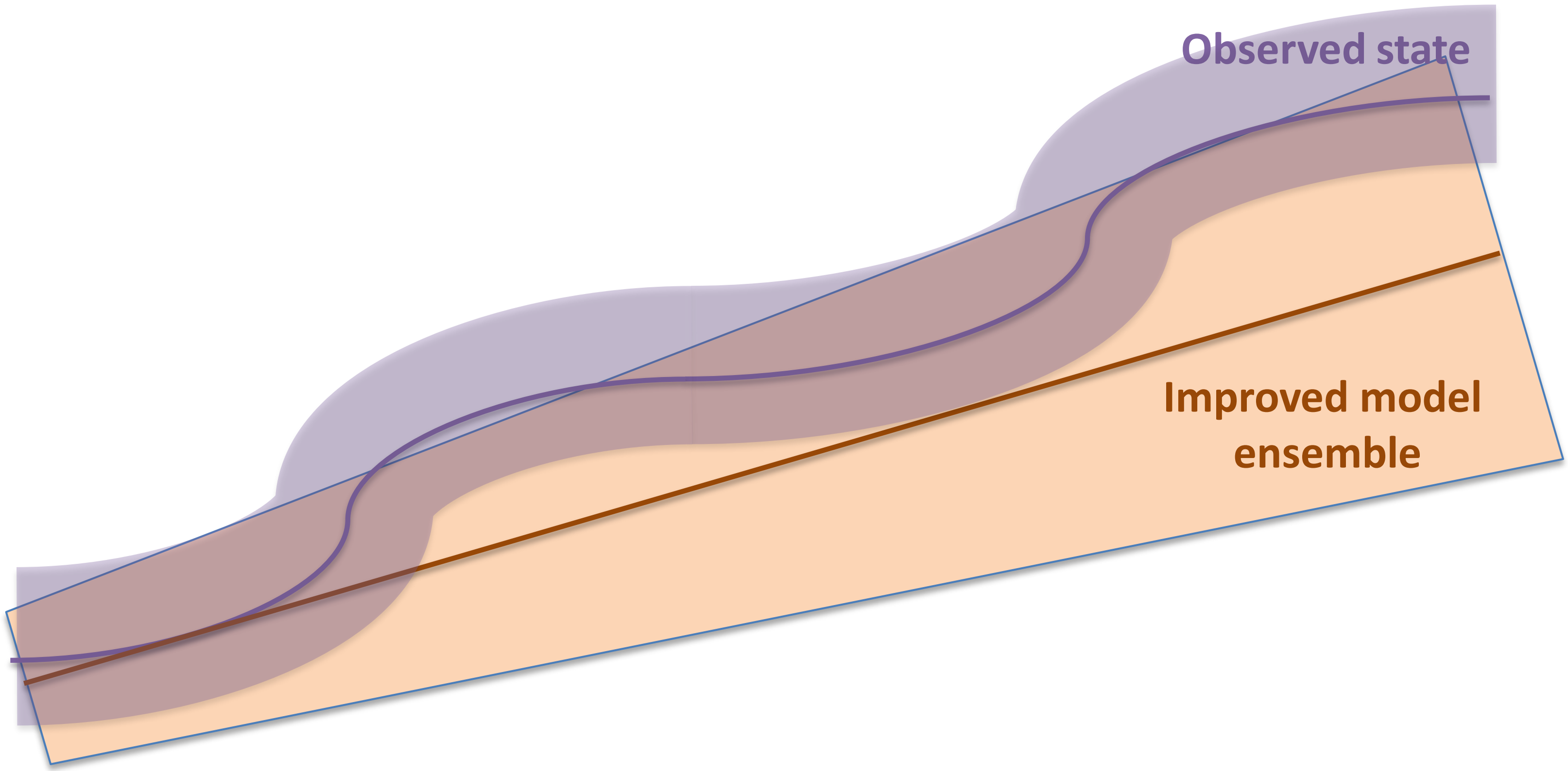
Cartoon of NCAR ensemble perturbation methods



SPPT leads to even greater dispersion, beginning much earlier in the forecast, but the ensemble mean is further from the observed state relative to the control. SPPT here requires calibration/tuning. Downside – some wild forecasts!

NCAR

If only we could just IMPROVE the model!



Reduce dependence on spread to compensate for a poor model trajectory, try to **improve the forecast model** to evolve more like the real atmosphere.

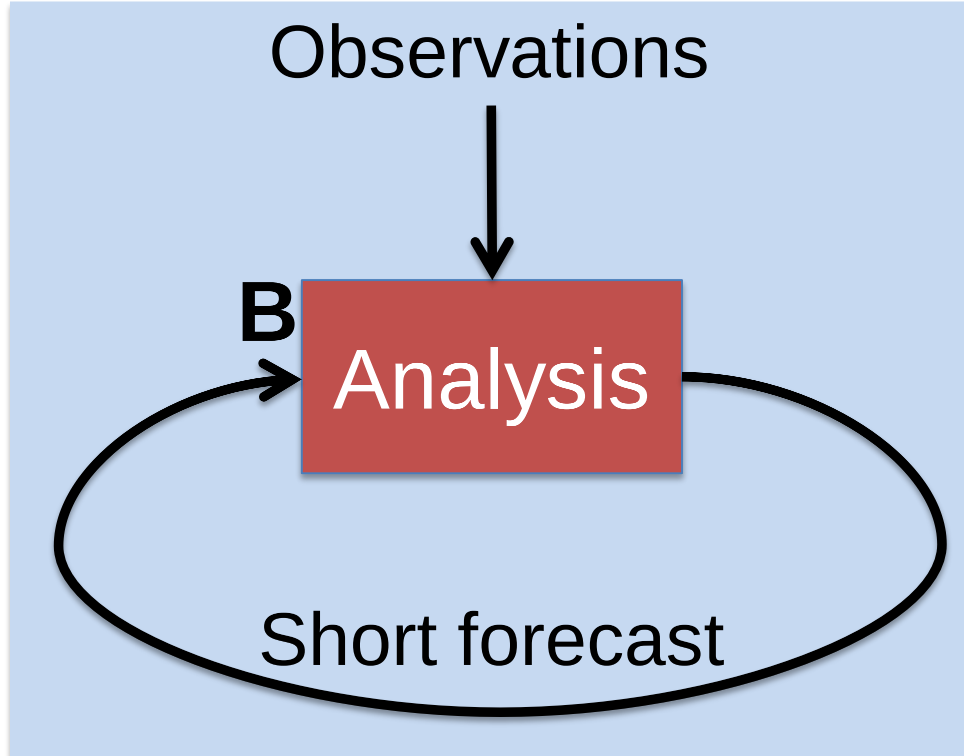
Then – find structural error growth deficiencies that require model error approaches to correct.

Model error diagnostics in continuously cycled analysis

Continuous cycling is 'best practice'

First guess (**B**) for analysis is short **forecast** from prior analysis

Minimal 'spinup' needed, near the model attractor

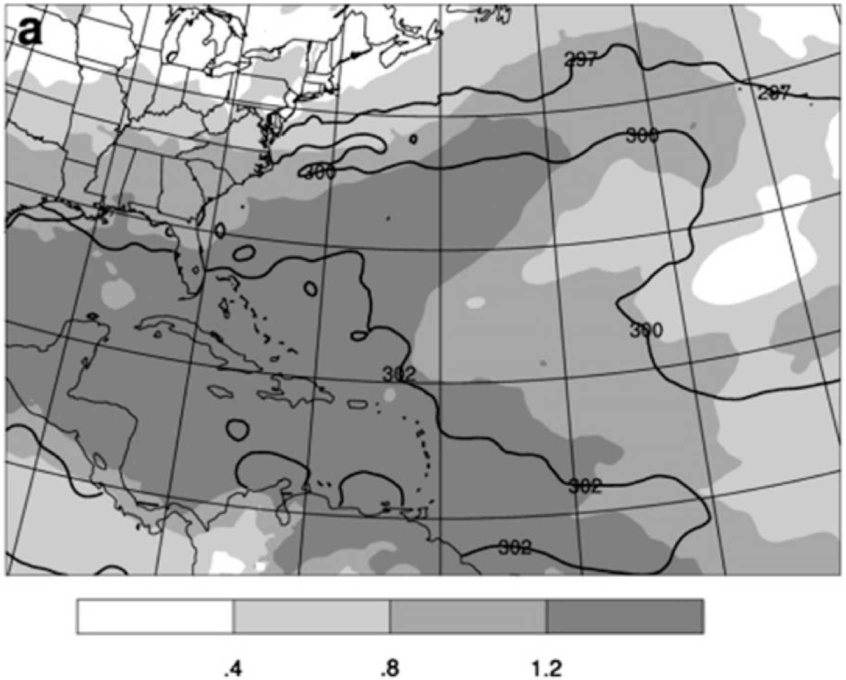


For regional models – nearly all centers use 'partial' cycling – periodically replacing the background from another (often global) analysis, adjustment to regional model climate can take days

Bad forecast model = degraded background for the analysis and forecasts

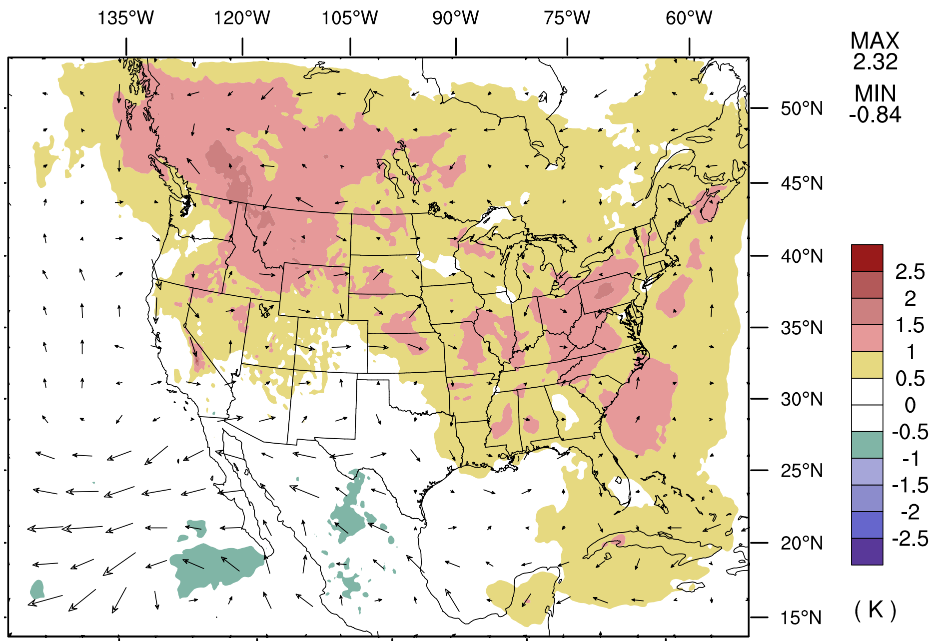
NCAR

Continuous cycled DA – model error revealed



700 hPa 1-month average temperature bias

Torn and Davis (2012)



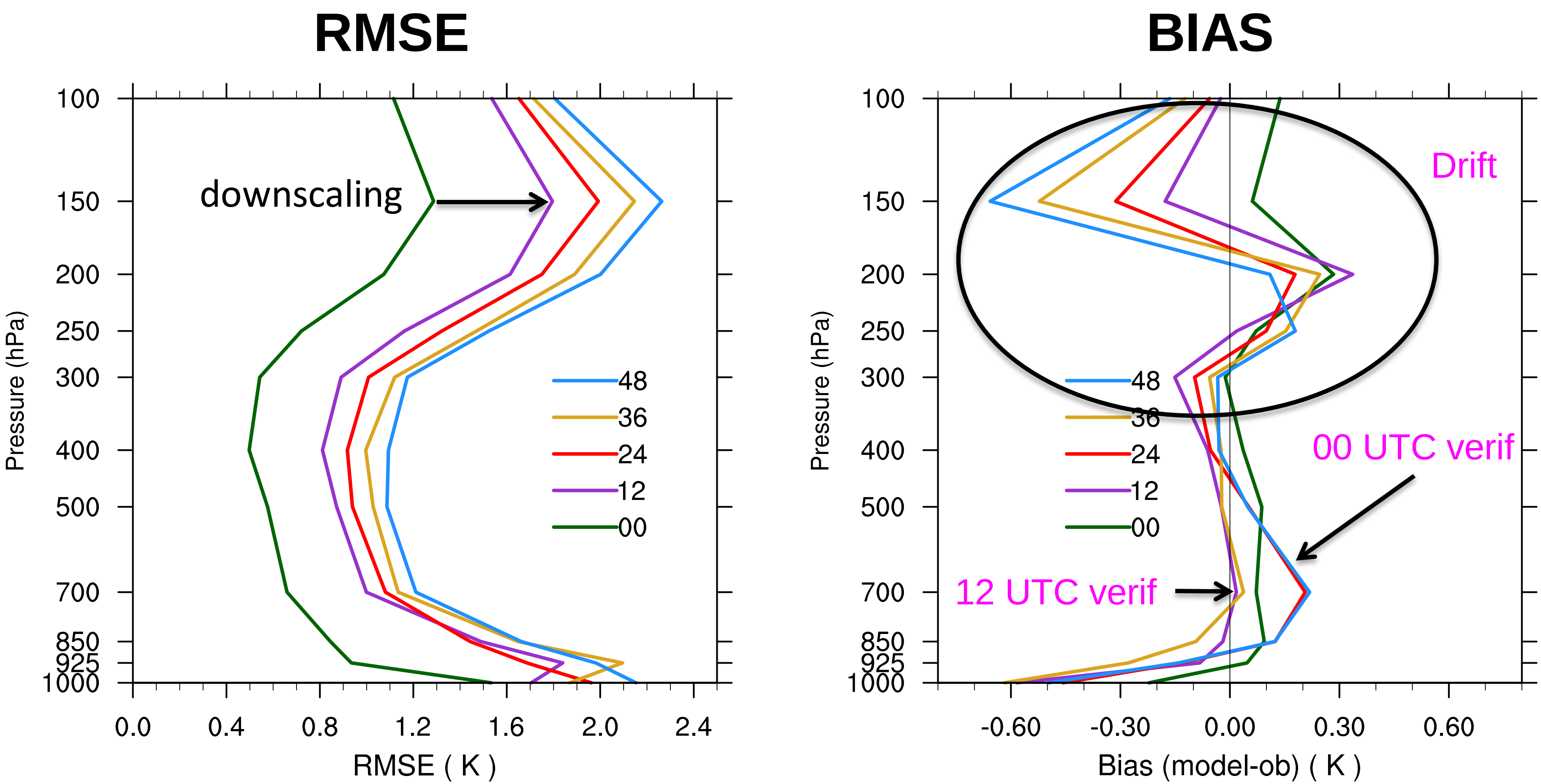
~ 700 hPa 35-day average temperature bias

Romine et al. (2013)

Identify model errors through continuous cycled DA – compare analyses against observations or other (trusted) analyses (GFS above).

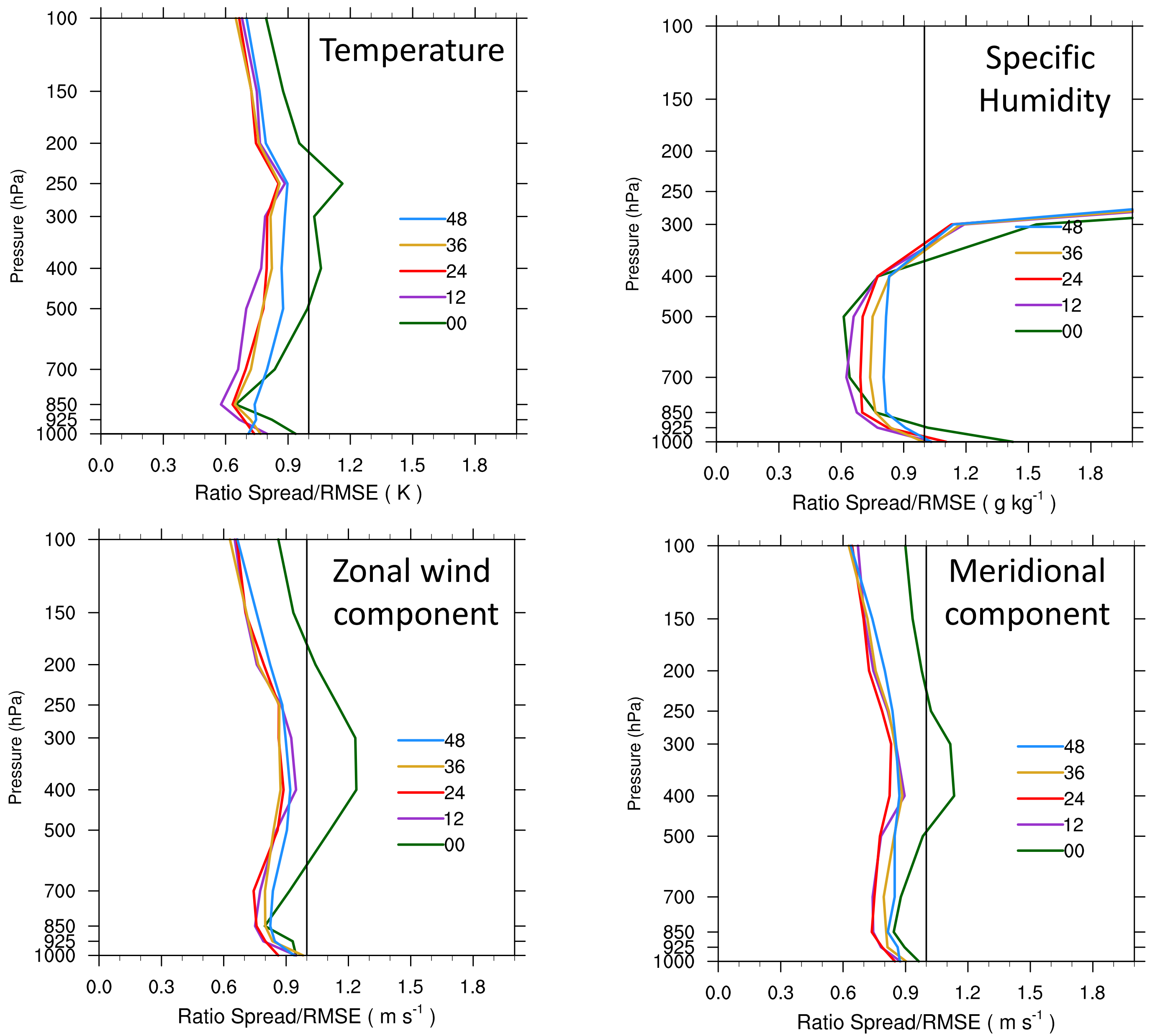
NCAR

Observation space verification



3-km ensemble forecast verification against rawinsondes
40 forecasts (late April to early June)
Initial down-scaling, diurnal bias in mid- and lower-troposphere, drift near tropopause

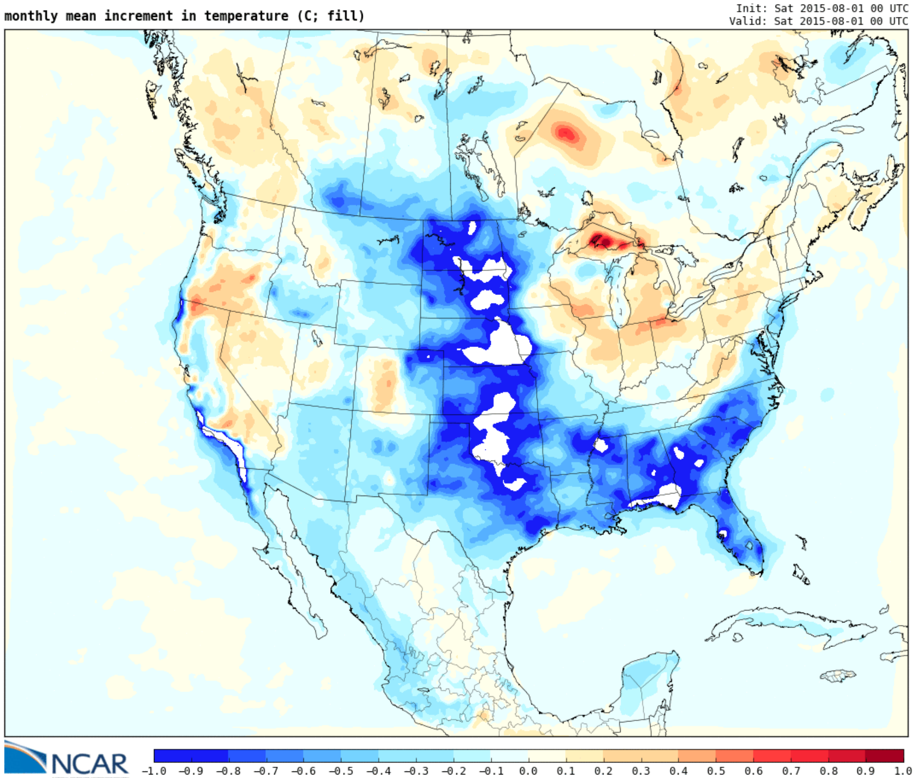
Spread-Error ratio during forecast



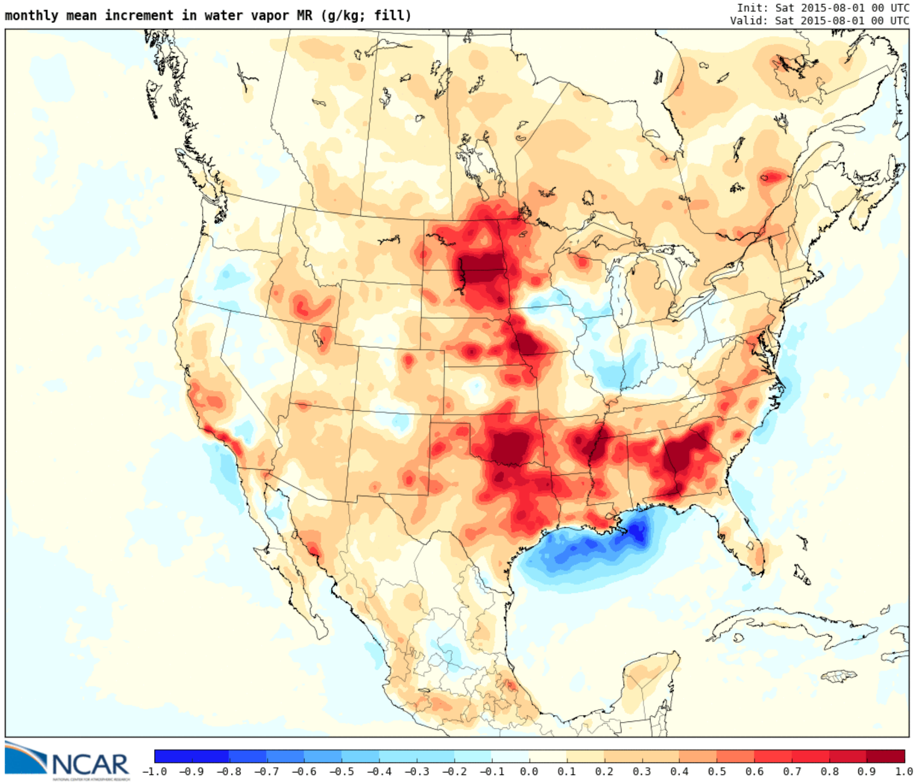
Real-time analysis mean innovations

August 2015 mean analysis innovations for 00 UTC

Lowest model level temperature



Lowest model level water vapor



MYJ PBL scheme for analysis system

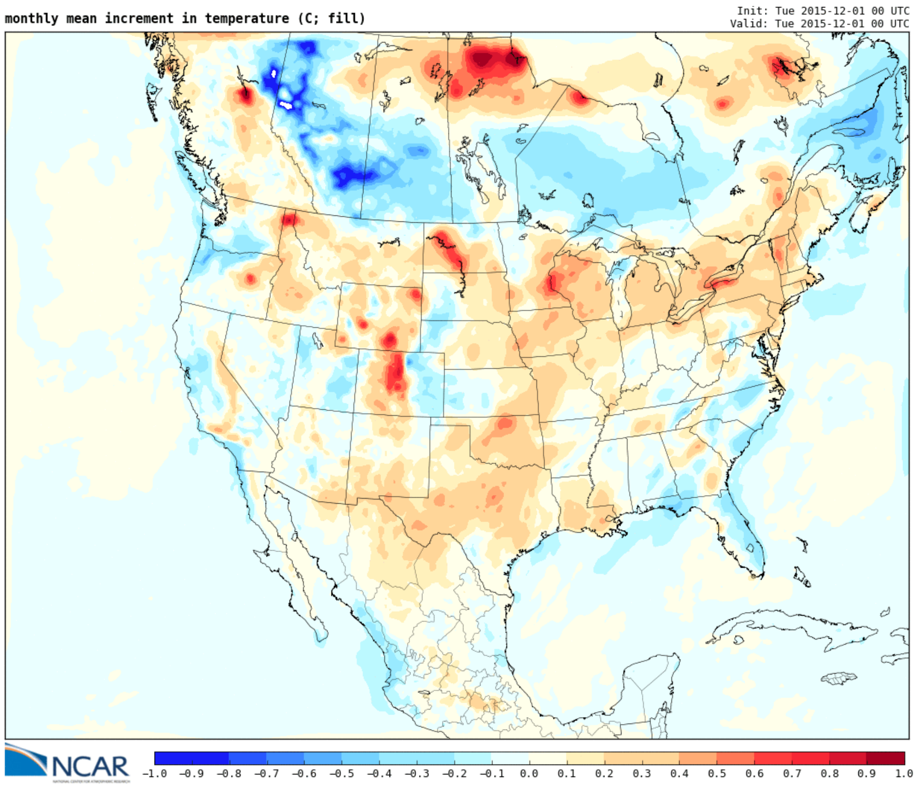
Classic cool and wet bias, but <u>not</u> everywhere

NCAR

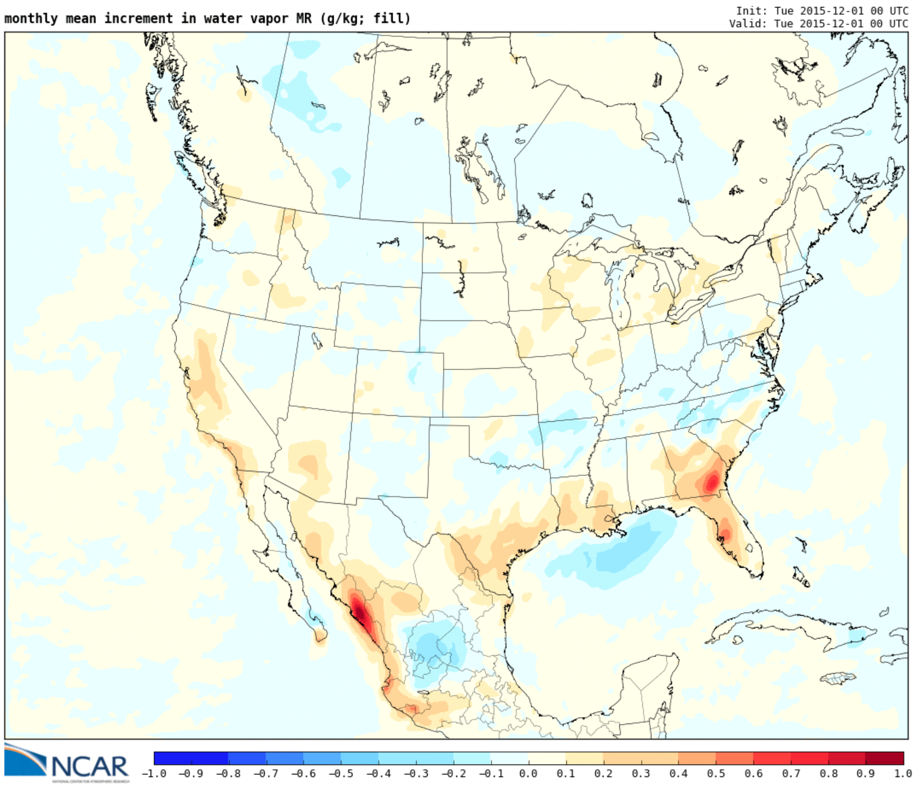
Real-time analysis mean innovations

December 2015 mean analysis innovations for 00 UTC

Lowest model level temperature



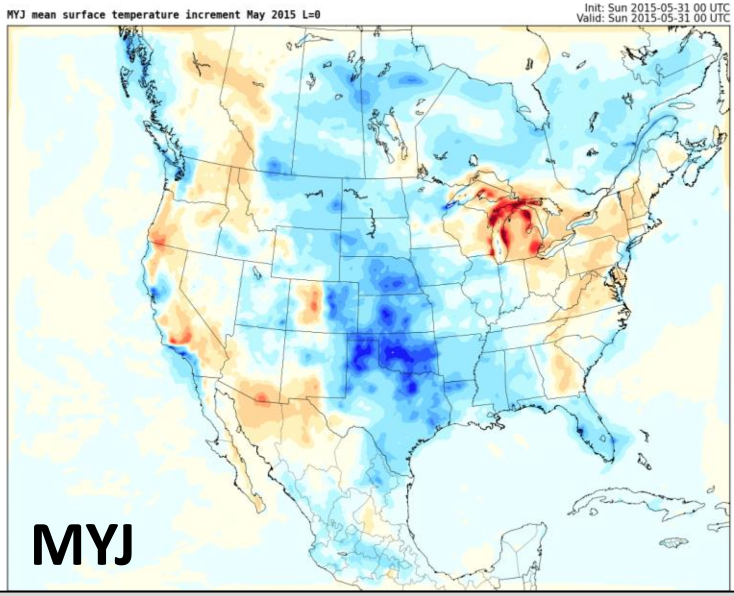
Lowest model level water vapor

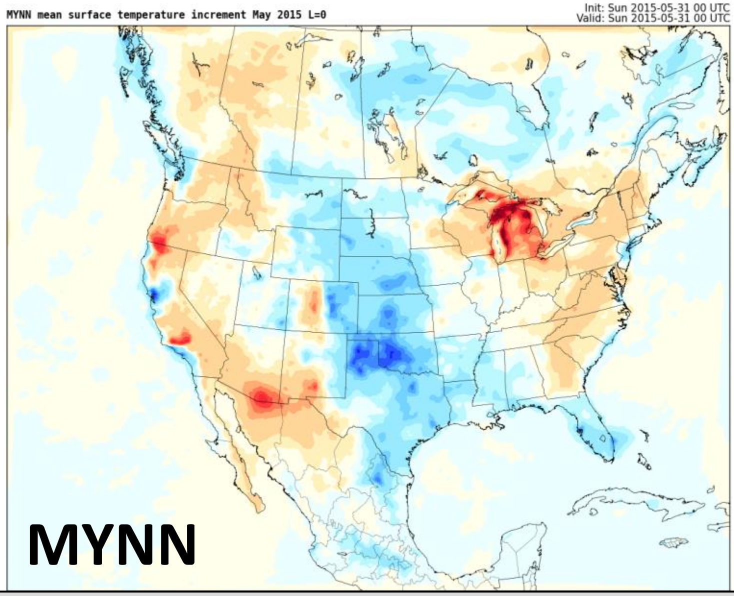


MYJ PBL scheme for analysis system

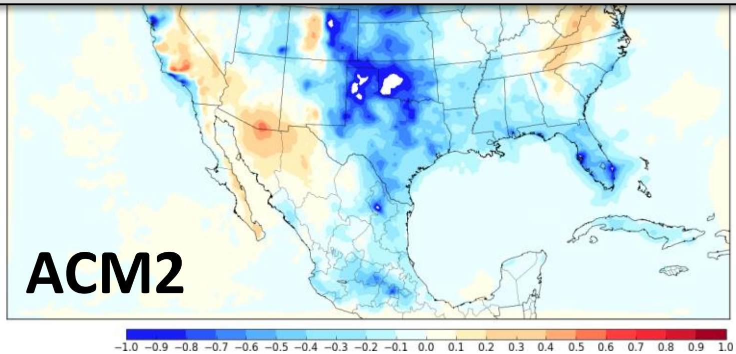
Slight warm bias in December but regional variability

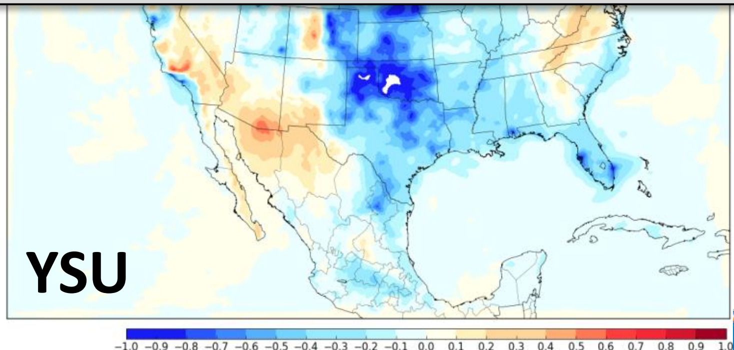
PBL physics – Surface T mean innovations – May 2015





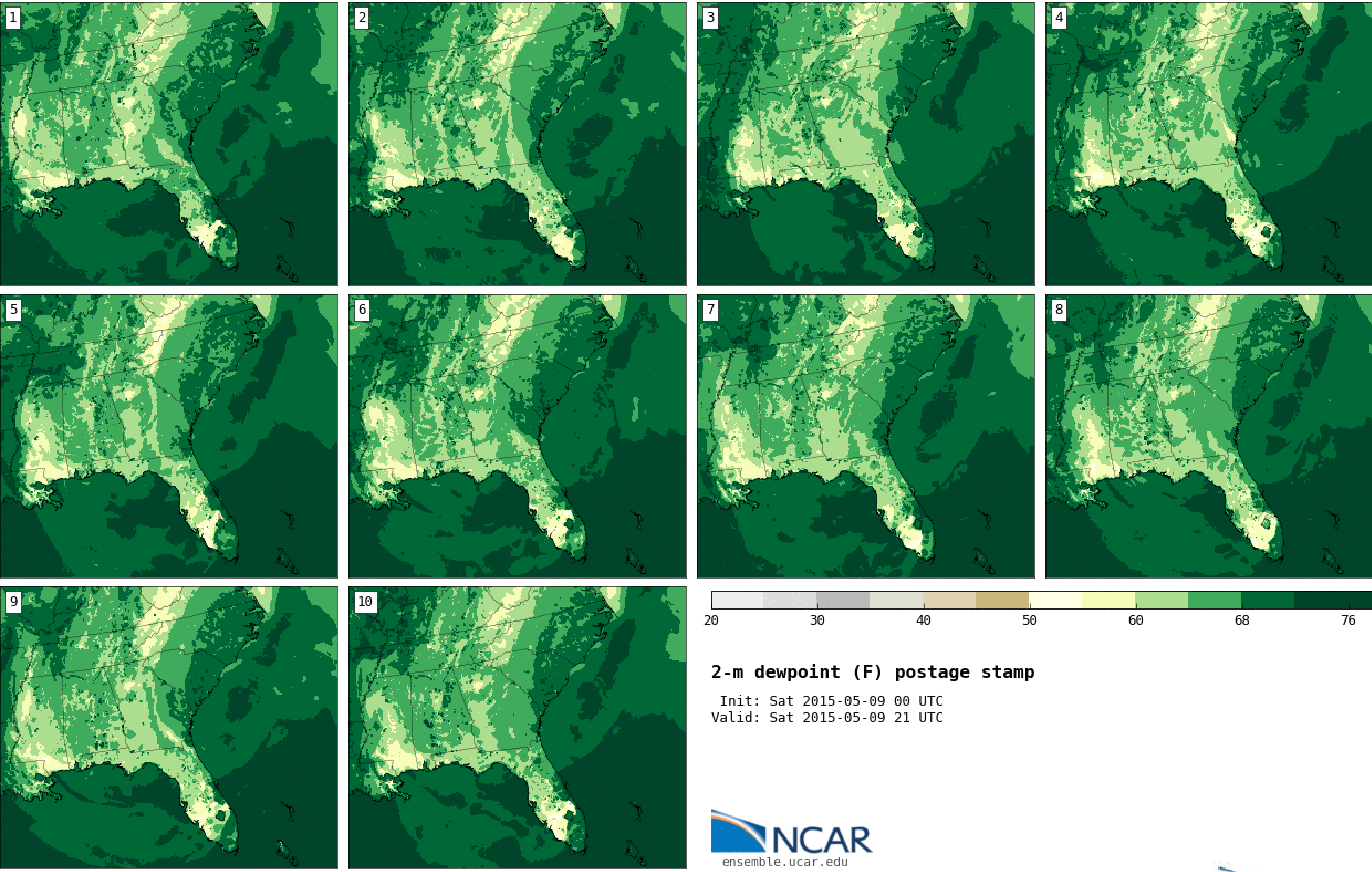
Systematic errors in surface temperature are only weakly dependent on PBL physics. Need to test surface physics.





NCAR

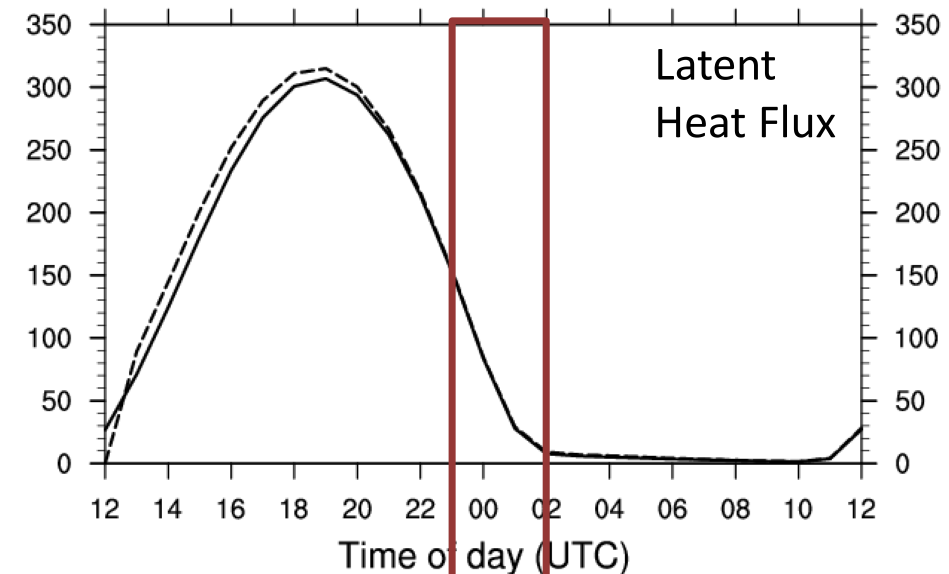
WRF model challenges – surface moisture

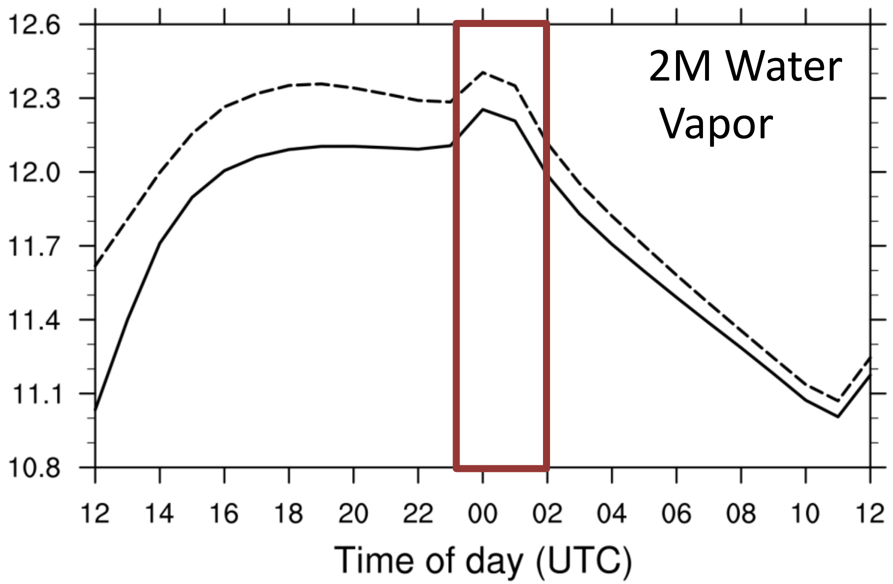


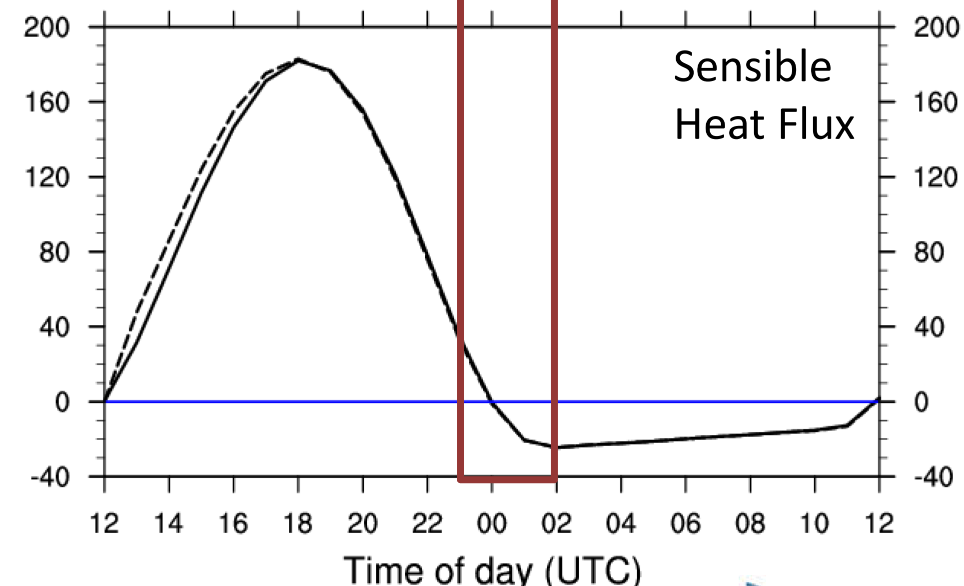
WRF model challenges – surface moisture

Spike in surface moisture owes to decoupling PBL while latent heat flux is still positive

Most prominent in heavily vegetated areas with calm winds

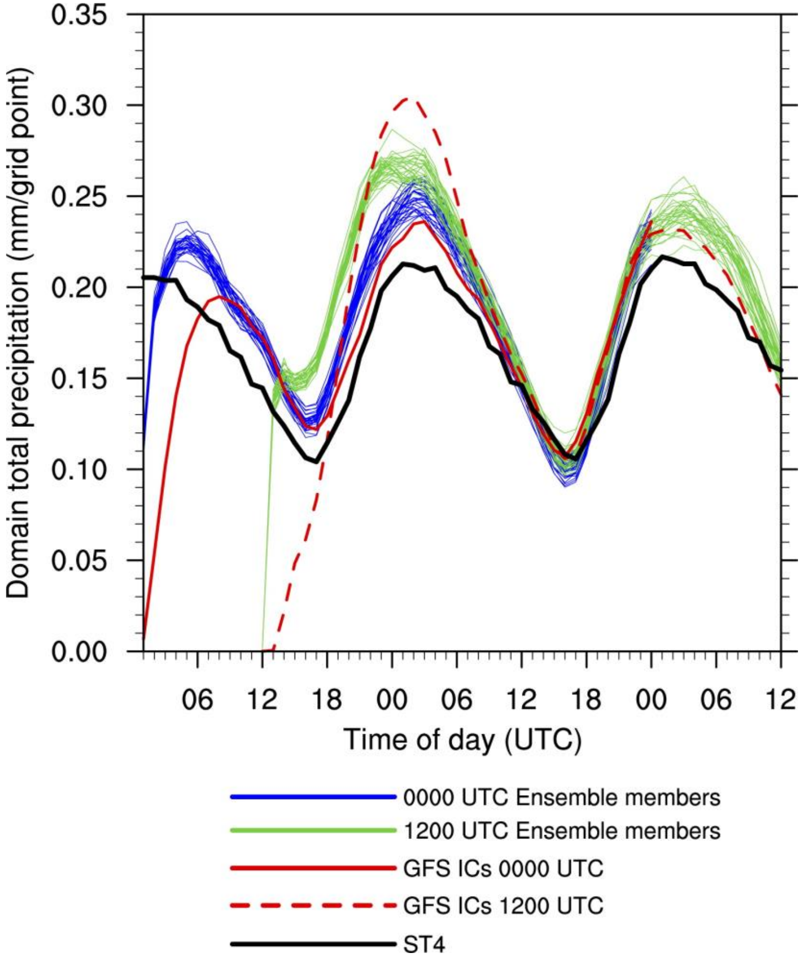




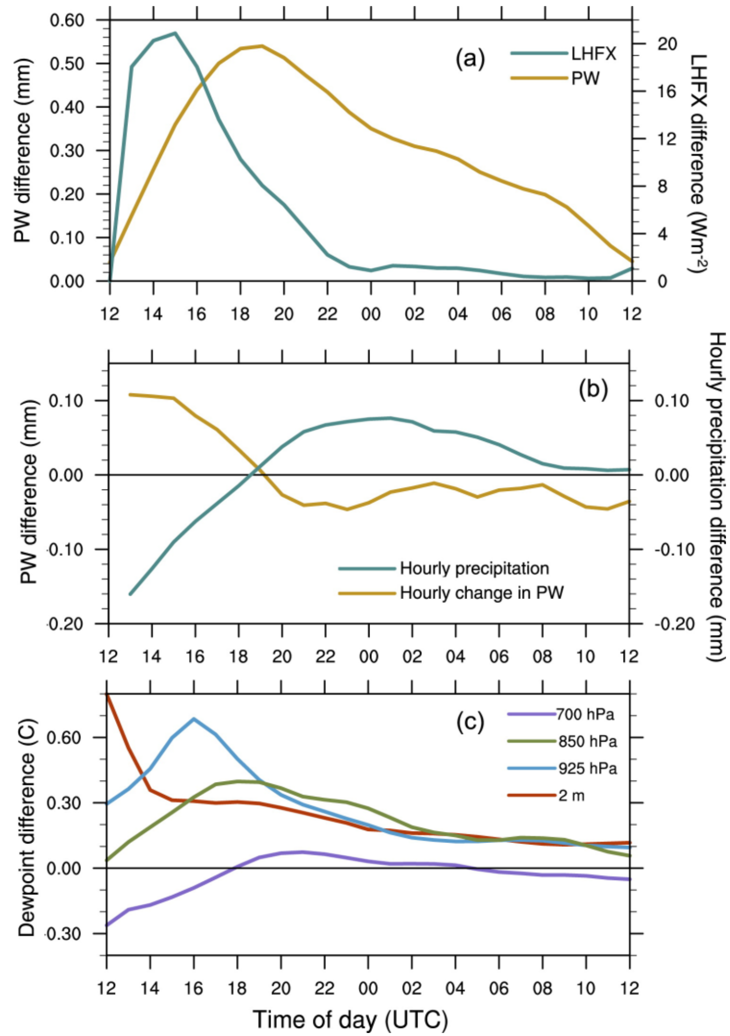


NCAR

Physics errors from downscaling



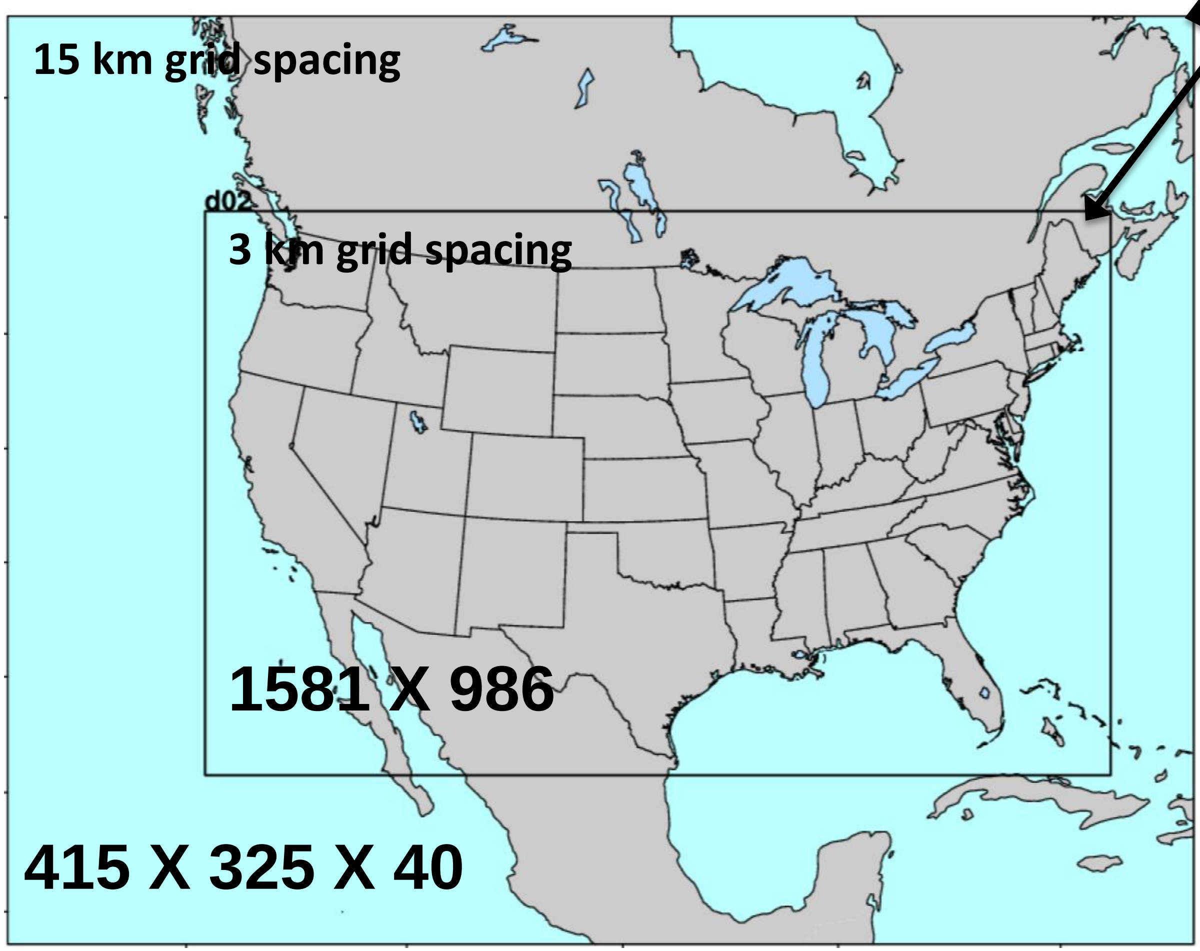
Ensemble 'warm start' 15-> 3 km
GFS 'cold start' 0.5 -> 3km



Difference in 12Z vs. 00Z GFS initialized forecast time series (avg over 30 days)

Schwartz et al. (2015)

Future: High resolution ensemble analysis



Analysis domain
(50 members)

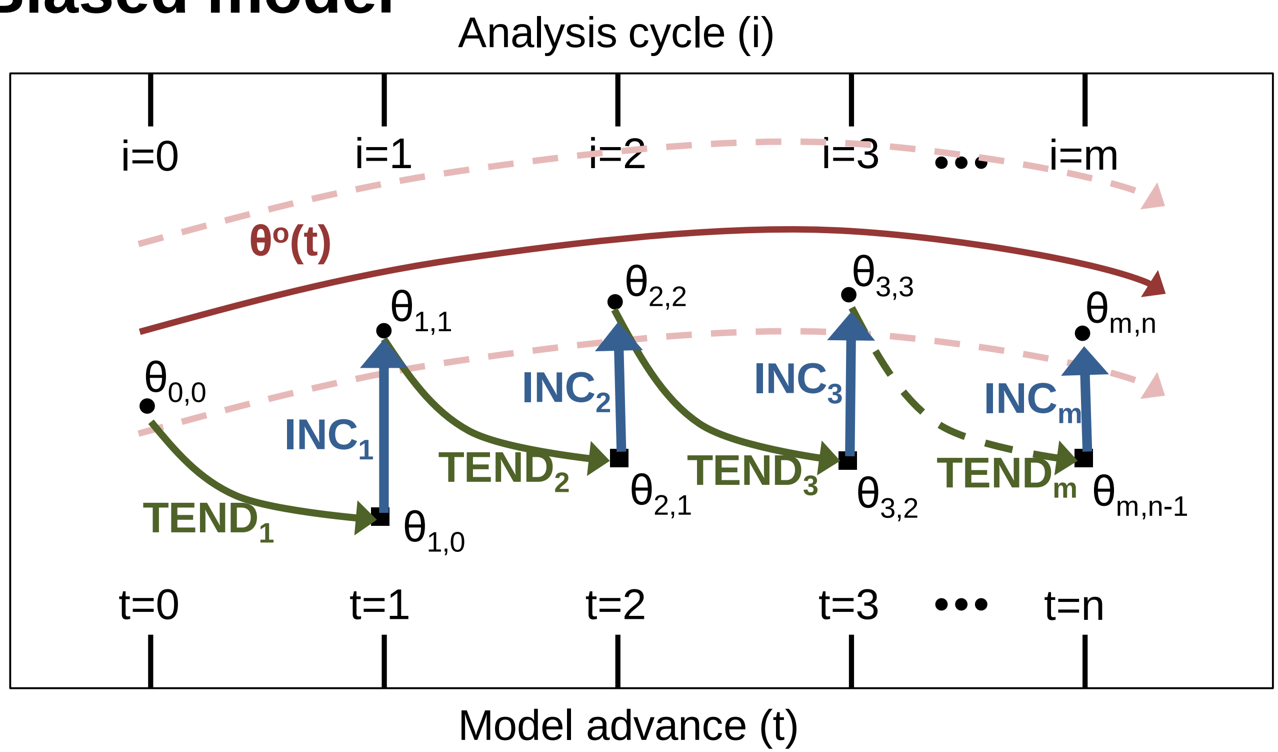
Avoid errors from downscaling, leverage convective scale observations, improve model climate (?). Eventually, global ensemble.

NCAR

Physics tendencies for further improvement

Demonstrated by S. Cavallo yesterday…

Biased model



$$\frac{1}{n}\sum_{i=1}^{n} INC_i \approx \frac{1}{m}\sum_{t=0}^{m} TEND_t$$

Adapted from Cavallo et al. (2016)

Summary – high resolution ensembles

Storm-scale ensemble design remains largely ad hoc:

- Stochastic methods to improve reliability
- Lots of opportunity to improve models at high-resolution prediction
- DA for high-resolution grids is still immature

Stochastic schemes are found to:

- improve ensemble dispersion characteristics
- introduce bias that may require additional spread
- difficult to verify adequate ensemble spread

- Effort is need to better target when and where additional spread is needed

NCAR

Improving/diagnosing model climatology

1) Continuously cycled DA (ongoing)
- Improve model climate toward obs/trusted analysis

2) Careful analysis/verification of forecasts (ongoing)
- Many examples the last few days, a few here as well

3) High resolution analysis grid (planned)
- Minimize physics and downscaling spinup errors
- Convective scale obs for analysis and **verification**

4) Physics tendency methods (planned)
- e.g., Rodwell, Cavallo talks
- Identify and correct error sources