



Ensemble systems and **high-impact** weather prediction applications

Glen Romine (NCAR)

Contributions from Soyoung Ha and May Wong

Workshop on Predictability and Uncertainty in Models and
Retrievals

Norman, OK

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Key considerations

- **For high-impact weather prediction:**
 - When, where, and how intense will the event be?
 - High-resolution model to 'resolve' convection
 - Computational constraints – so regional domain
 - Target skill/reliability for short-term window (e.g., 0-36 h)
- **A push toward model unification**
 - Single dynamic core to simplify support and development, physics suites, interfaces, same prediction systems for global and regional (e.g., FV3, MPAS)
- **Maintain good spread – error relationship** throughout prediction
 - **Dominated by model errors and inadequate growth of model errors**
 - **Would need less error growth with a better forecast model**
- **Visualization and Verification**
- **Research applications of formal CAM ensembles**

Current state of 0-36 hr CAM ensemble prediction

- HREFv2 operational convection-allowing model (CAM) ensemble
 - Operationalized storm-scale ensemble of opportunity
 - Conglomeration of well-tuned 3-km deterministic model forecasts
 - NAM nest, NSSL-WRF, NMMB, ARW
 - multi-model, time-lag (0,-12 h), multi-IC
 - Performs quite well for 'next-day' prediction applications (12-36 h)
- 'Formal' CAM ensembles
 - Purposefully designed, e.g. former NCAR ensemble
 - Best practice in ensemble design still a work in progress
 - Current state: similar or worse skill and lower reliability than HREFv2

Prediction challenges suitable for CAM ensembles



Convection (e.g., initiation/timing, hazards, intensity)



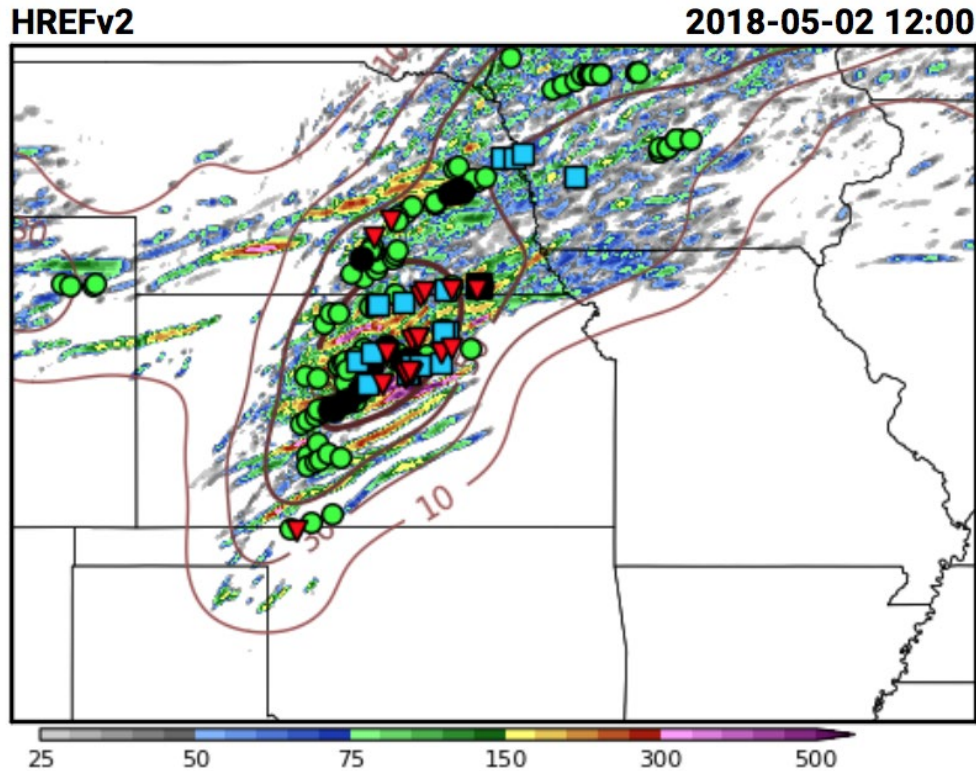
Winter weather (e.g., timing, accumulation rates, type)



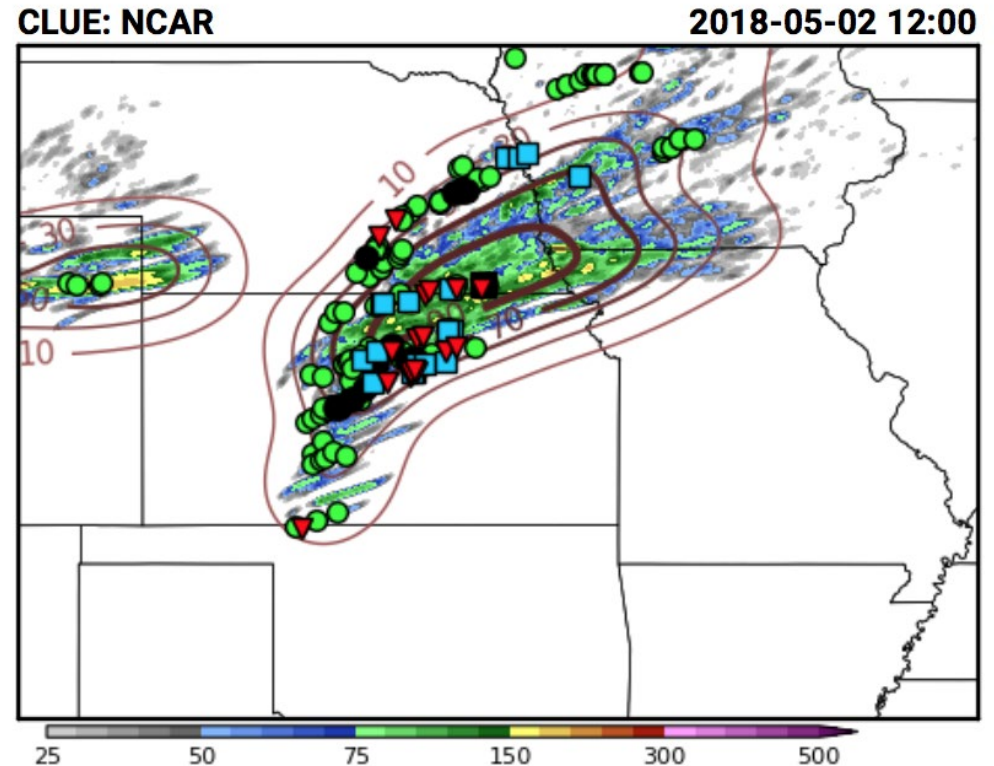
Fire weather, wind storms, air quality, transportation

Ensemble max UH, storm reports: POD vs. FAR

HREF multi-model



NCAR HRRRE: single dynamic core



HREF (left)
NCAR HRRRE (right)
Updraft Helicity
12-36 h forecast

tornado, hail,
and wind reports

Graphics from Brett Roberts Hazardous Weather Testbed

Elements in formal CAM ensemble design

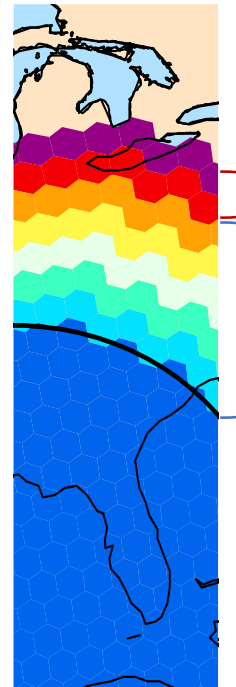
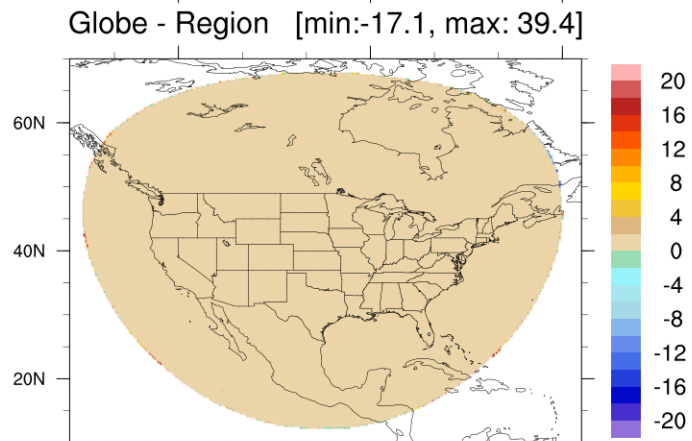
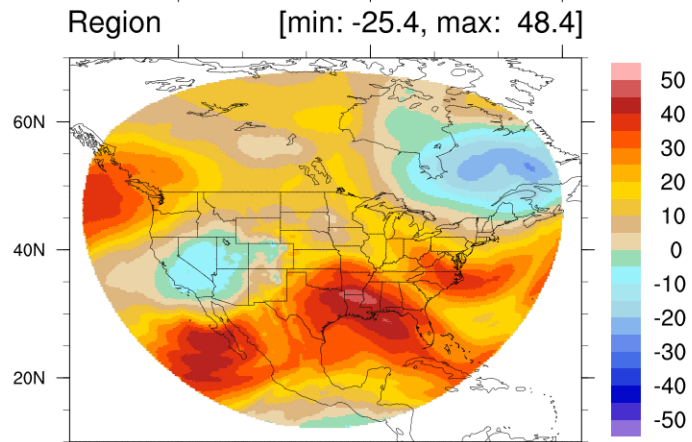
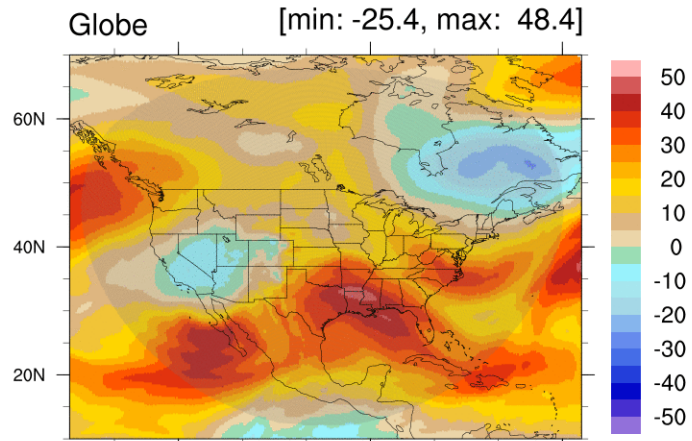
- **Initial condition uncertainty**
 - Flow-dependent background/analysis errors (e.g., initialized from EnKF analysis)
 - Time lag
 - Multi-analysis (e.g., GFS ensemble)
 - Inflation options in analysis system
- **Boundary condition uncertainty**
 - Lateral (from external) and lower boundary uncertainty (LSM, SST)
- **Model error representation**
 - Multi-model
 - Multi-physics
 - Multi-parameter
 - Stochastic methods (e.g., SKEBS, SPPT, SPP)

CAM ensemble initial and lateral boundary conditions

- Would like to have:
 - All members equally likely
 - Flow-dependent perturbations
 - Appropriate spread skill (e.g., low [high] spread indicates high certainty [uncertainty]), which persists into the forecast
 - Smooth transition from analysis into the forecast
- Ensemble DA provides flow-dependent errors for ICs, but may not lead to optimal error growth (area of active research)
 - Sensitive to inflation options, additive noise
- Lateral boundary conditions should include errors – ideally flow dependent

CAM lateral boundary conditions

Regional MPAS

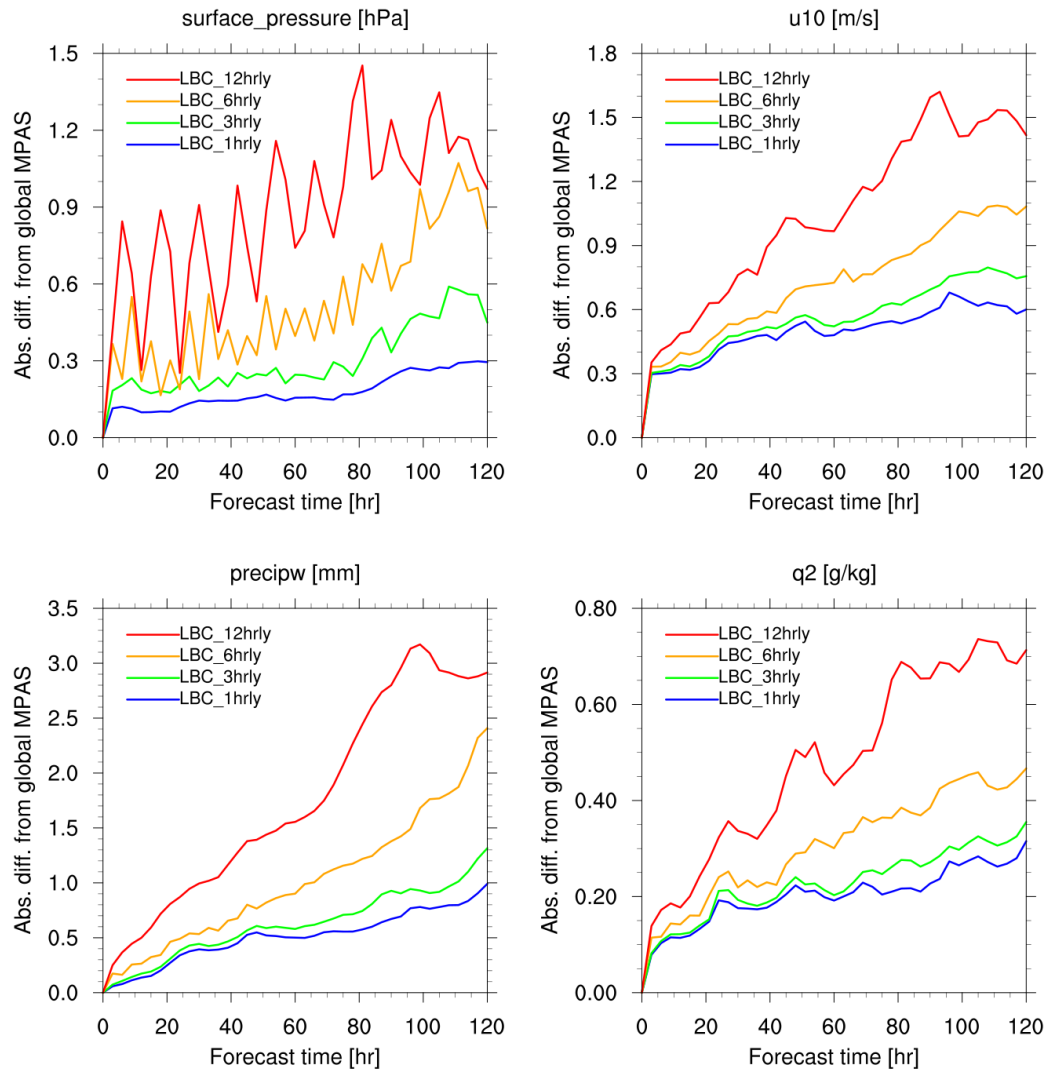


- The same model as in global forecasts: no discrepancy in physics and dynamics
- **No artifacts or reflection along the lateral boundaries for inflow and outflow!**
- In this test, physics versions were slightly different between global and regional MPAS.

From S. Ha

LBC update frequency errors

Regional MPAS forecasts from FNL analysis at 2017-04-28_00UTC



LBC errors minimized with frequent updates

Additional sources of error:

- changes in model climate (including physics) across boundary
- changes in grid resolution

Optimal for regional CAMS:

- Flow-dependent errors at LBC
- Regional domain of adequate size

Lower boundary condition diversity also important to promote BL error growth

Ensemble model error representation

None

Rely on lateral boundary perturbations and initial condition diversity
e.g., downscalers from global ensembles

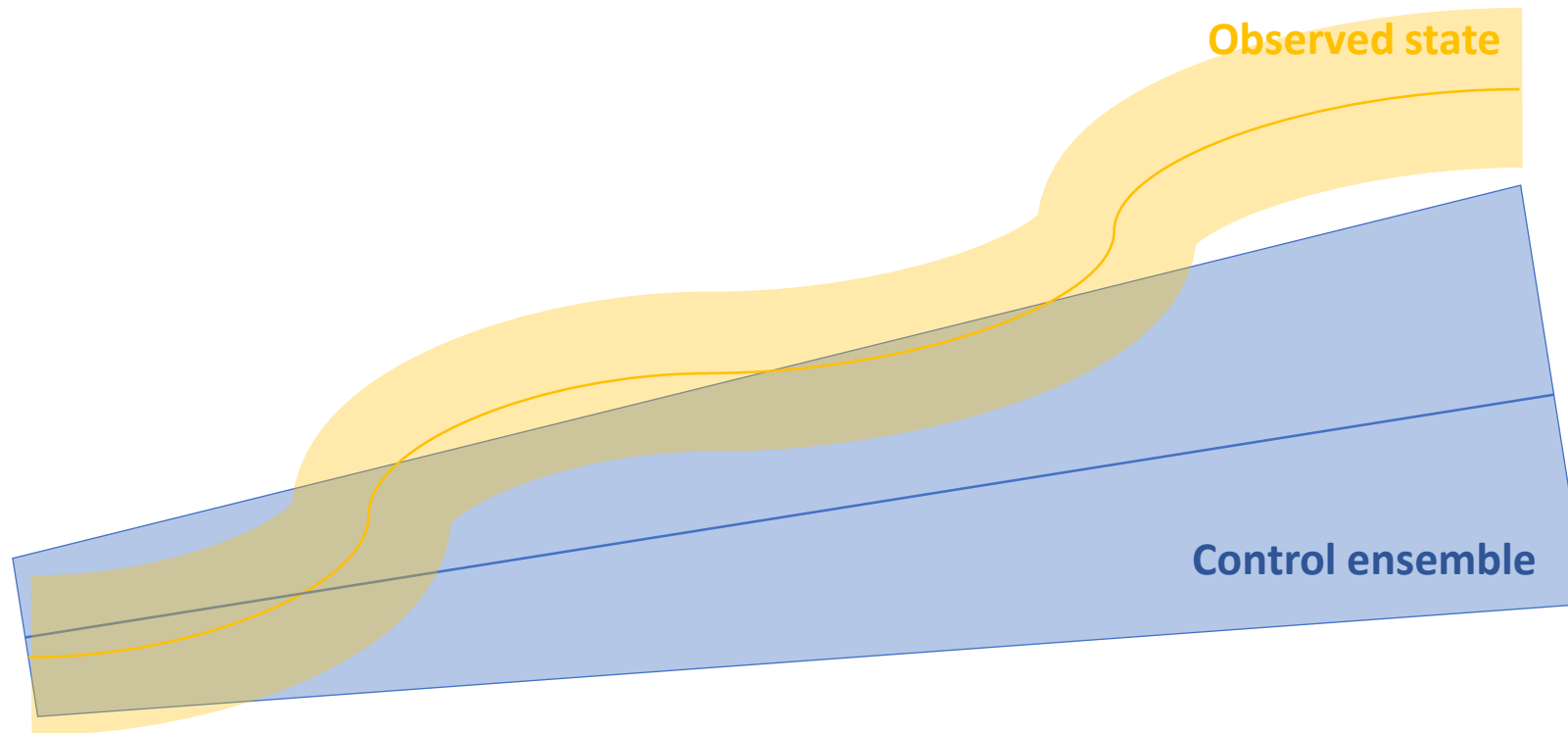
Multi-model/multi-physics/multi-parameter

- Uncertain representations of physical processes
- 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 – *designed for global model applications*
- Single physics climate
- Options available in WRF-ARW:
 - 1) Stochastic Kinetic Energy Backscatter Scheme (SKEBS)
 - 2) Stochastically Perturbed Parameterization Tendencies (SPPT)
 - 3) Stochastic perturbed parameters (SPP)

Cartoon of CAM ensemble perturbation methods



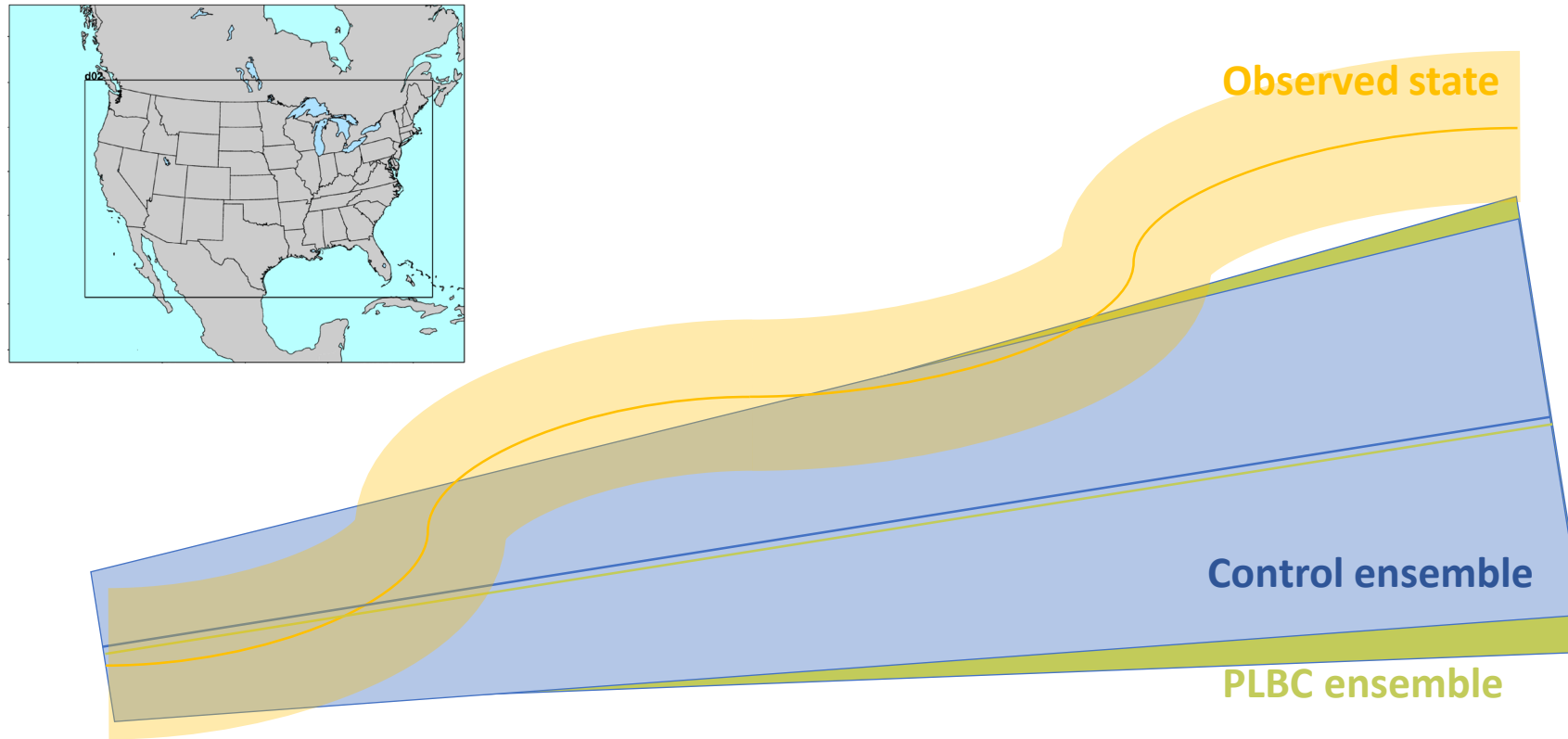
Control ensemble:

- Roughly approximates true evolution of the atmosphere, unknown exact truth
- Lacks sufficient dispersion to capture the observed evolution after short integration

Select options:

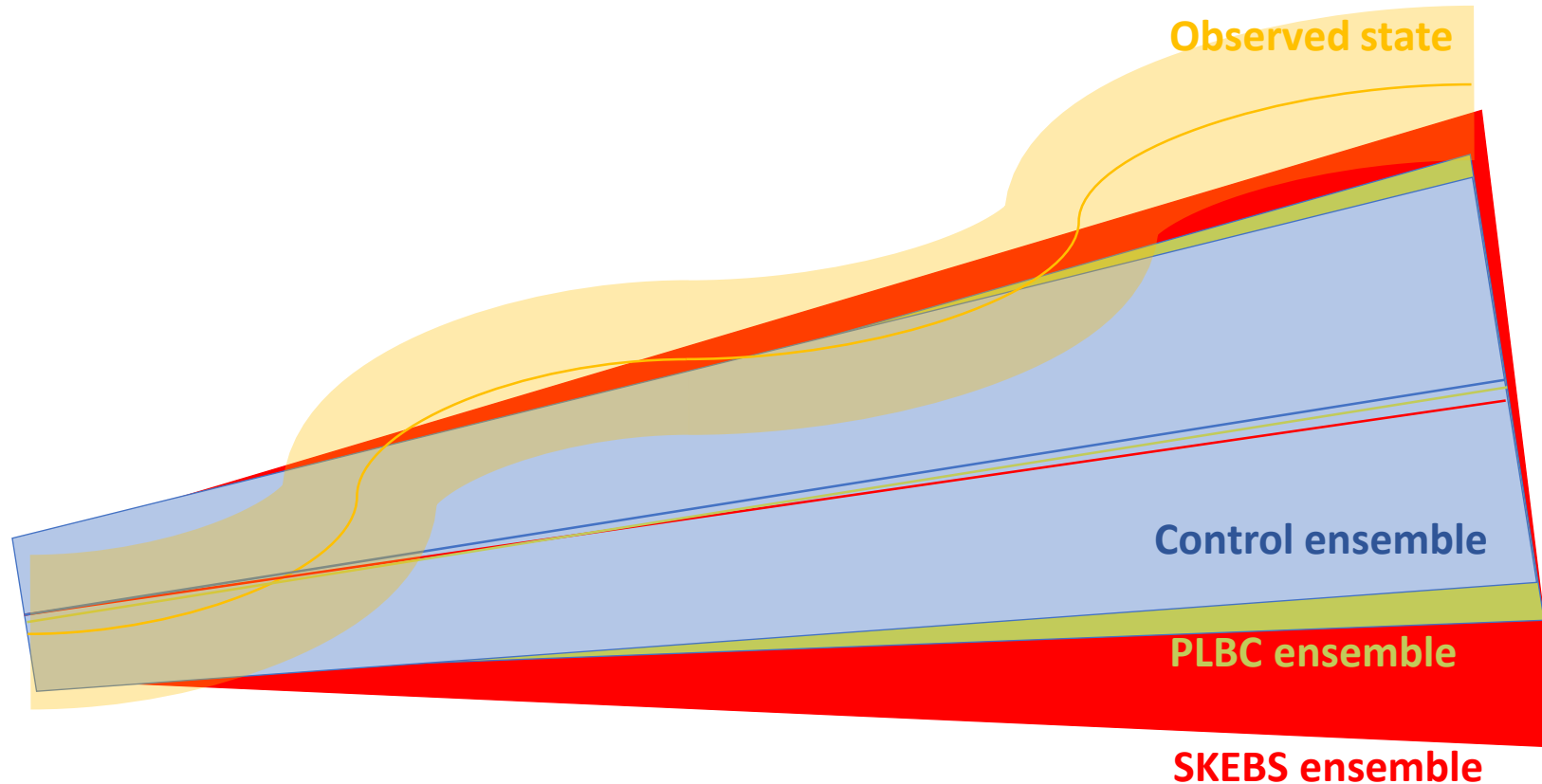
Multi-XXX, calibration, perturbed boundaries, stochastic methods

Cartoon of CAM ensemble perturbation methods



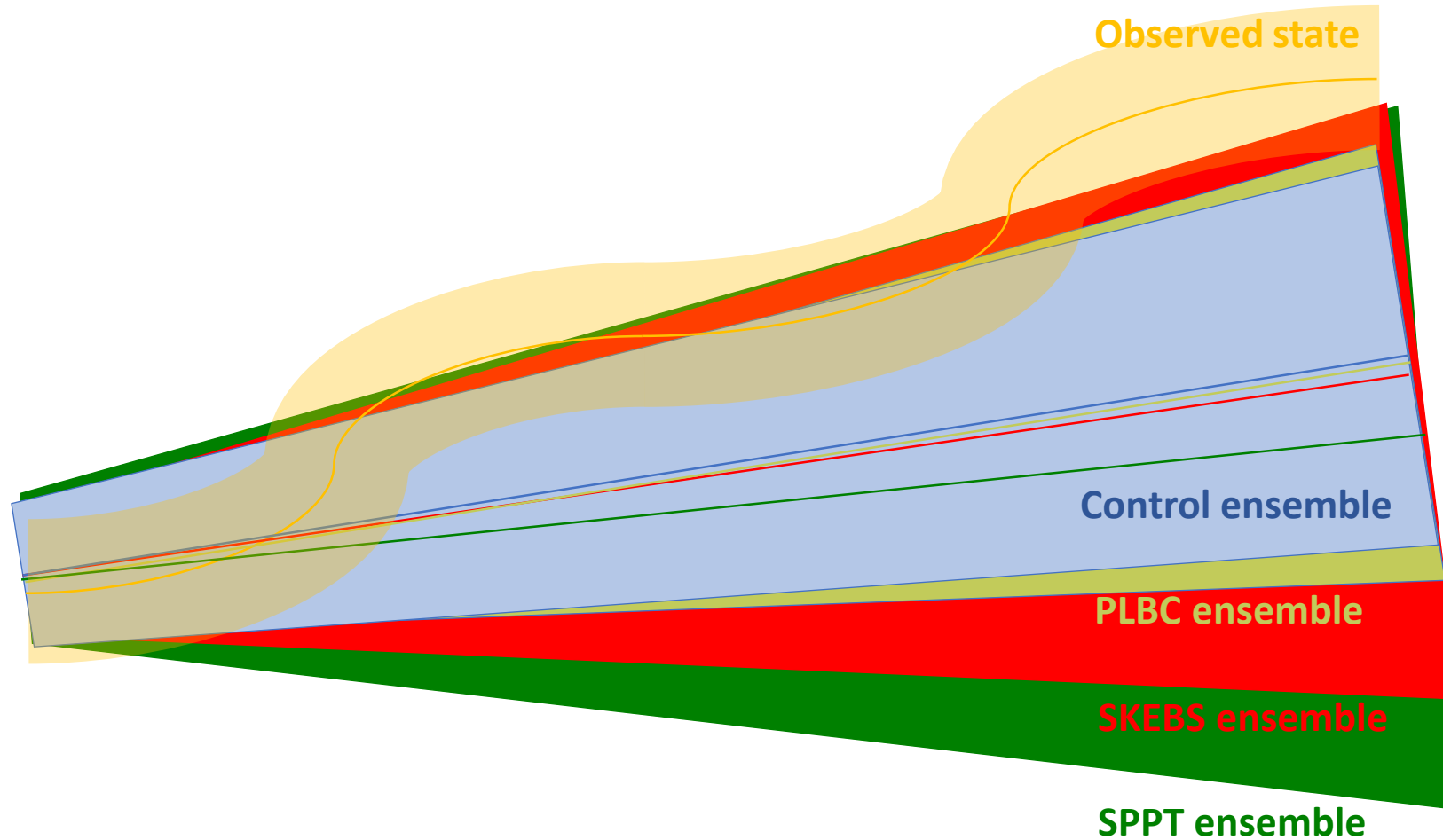
Perturbing the lateral boundary condition improves spread somewhat, but later in the forecast owing to the nested design. Ensemble mean stays about the same.

Cartoon of CAM ensemble perturbation methods



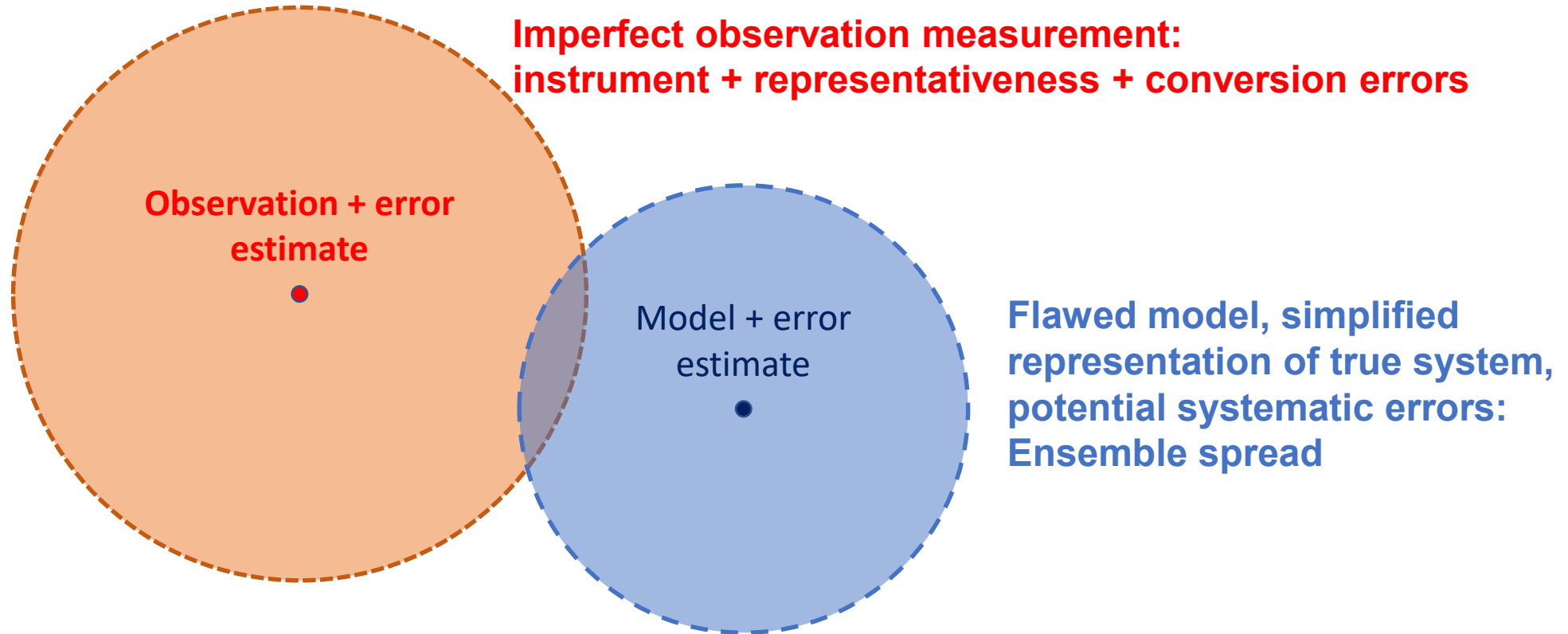
SKEBS leads to greater dispersion, beginning earlier in the forecast, with nearly the same ensemble mean as the control and perturbed boundary ensemble.

Cartoon of CAM ensemble perturbation methods



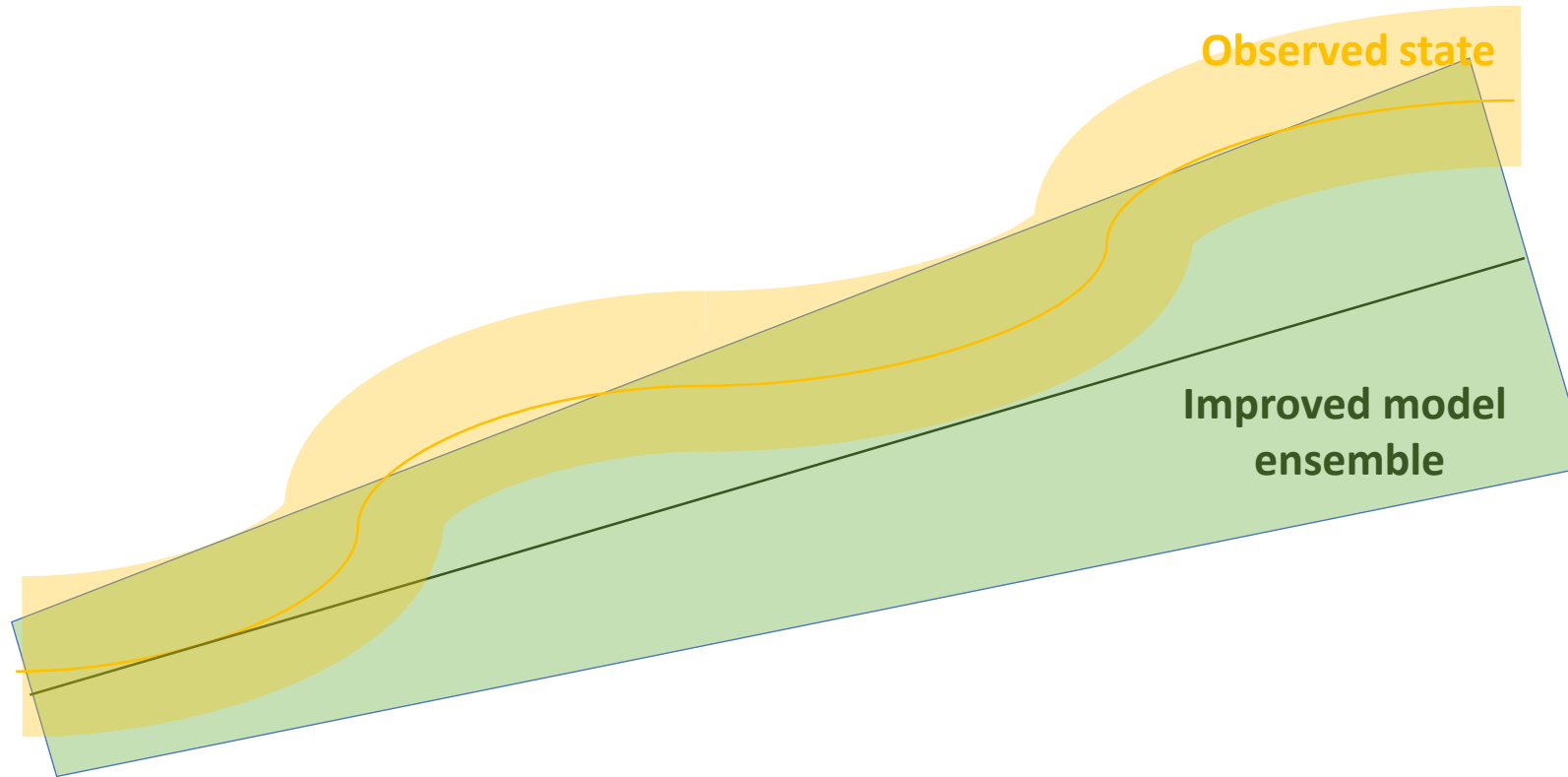
SPPT leads to even greater dispersion, beginning much earlier in the forecast, but the ensemble mean is further from the observed state relative to the control. See Romine et al. 2014

Imperfect observations, flawed forecast model



- These states are effectively indistinguishable despite minimal overlap
- DA can be used, with sufficient observations, to pull toward the observed state, but will drift to model attractor during the forecast
- In cycled DA, model errors can be time averaged to identify systematic problems

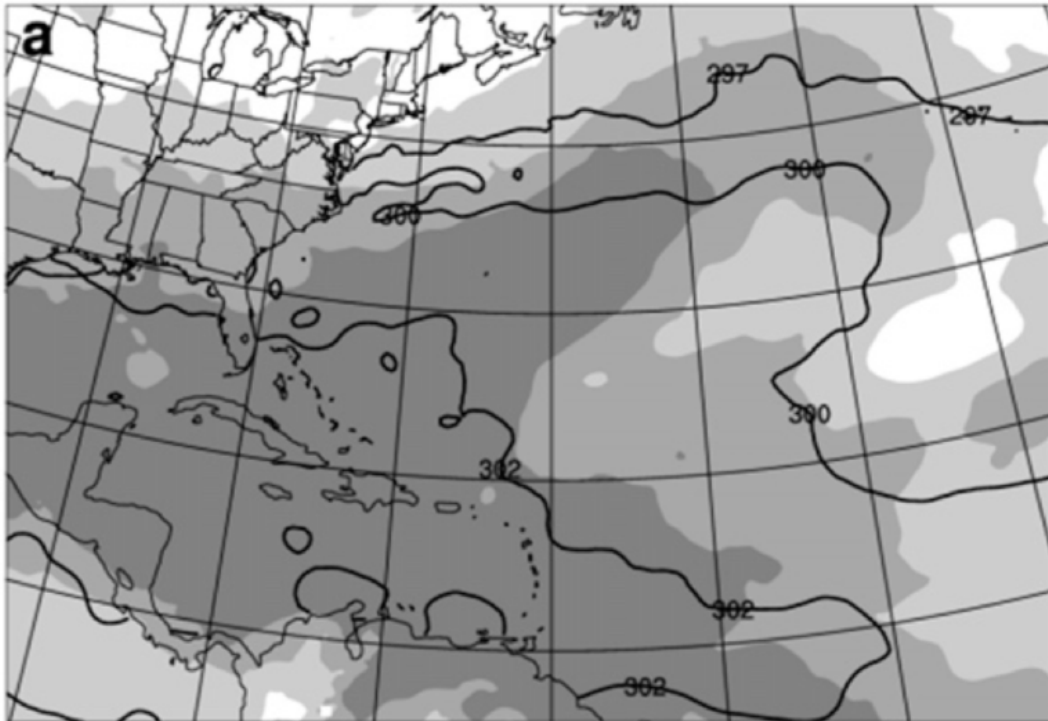
Alternative – IMPROVE the model!



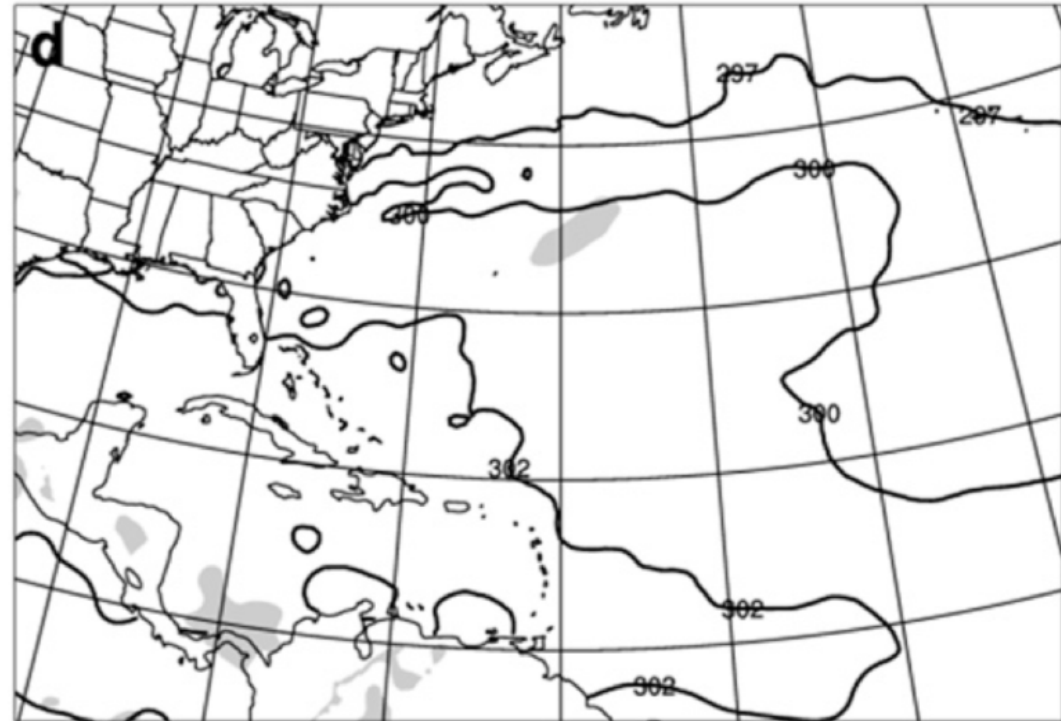
Instead of relying on spread to compensate for a poor model trajectory, try to **improve the forecast model** to evolve more like the real atmosphere. **Sounds great, but difficult in practice.**

Model error – cycled data assimilation

Kain-Fritsch cumulus scheme



Tiedtke cumulus scheme

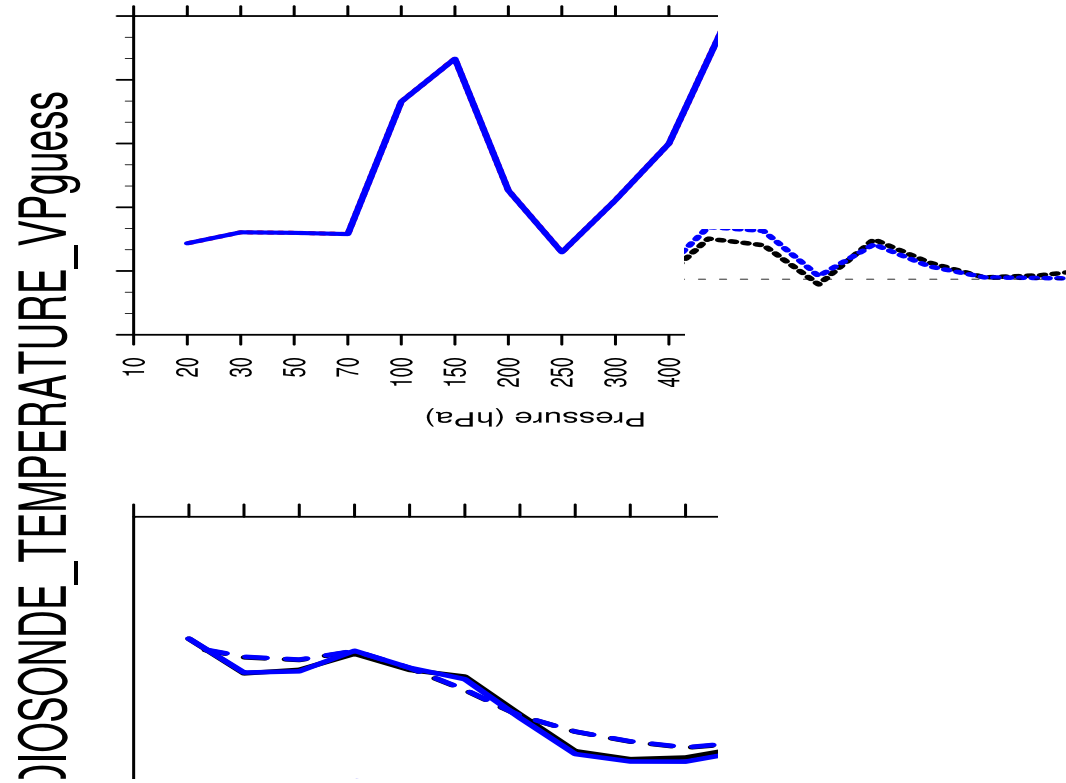


700 hPa temperature difference in 6 hr forecasts from GFS analyses – shallow cumulus scheme

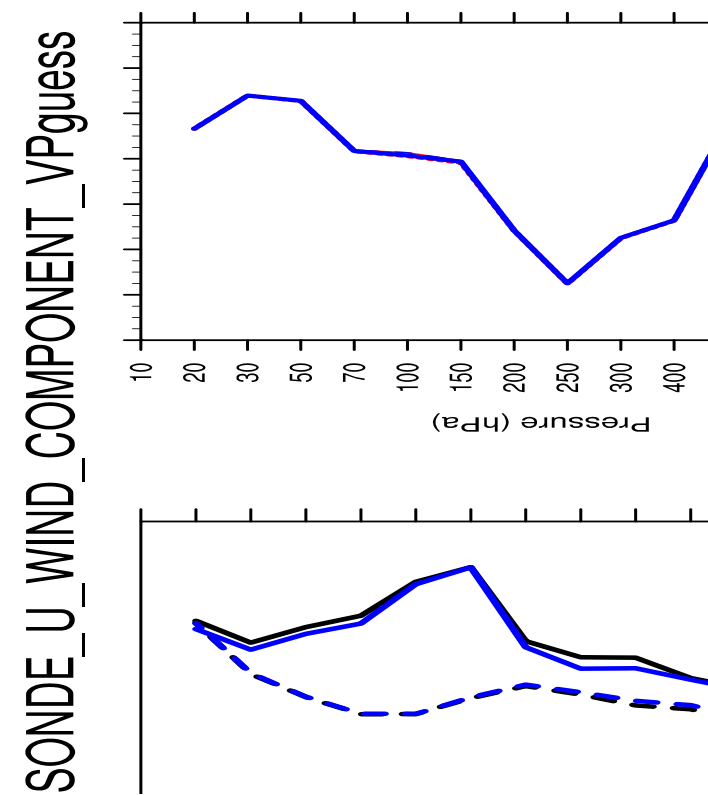
See Torn and Davis 2012, Romine et al. 2013

Model error – NCAR ensemble vs. HRRR physics

Radiosonde temperature fit to prior analysis

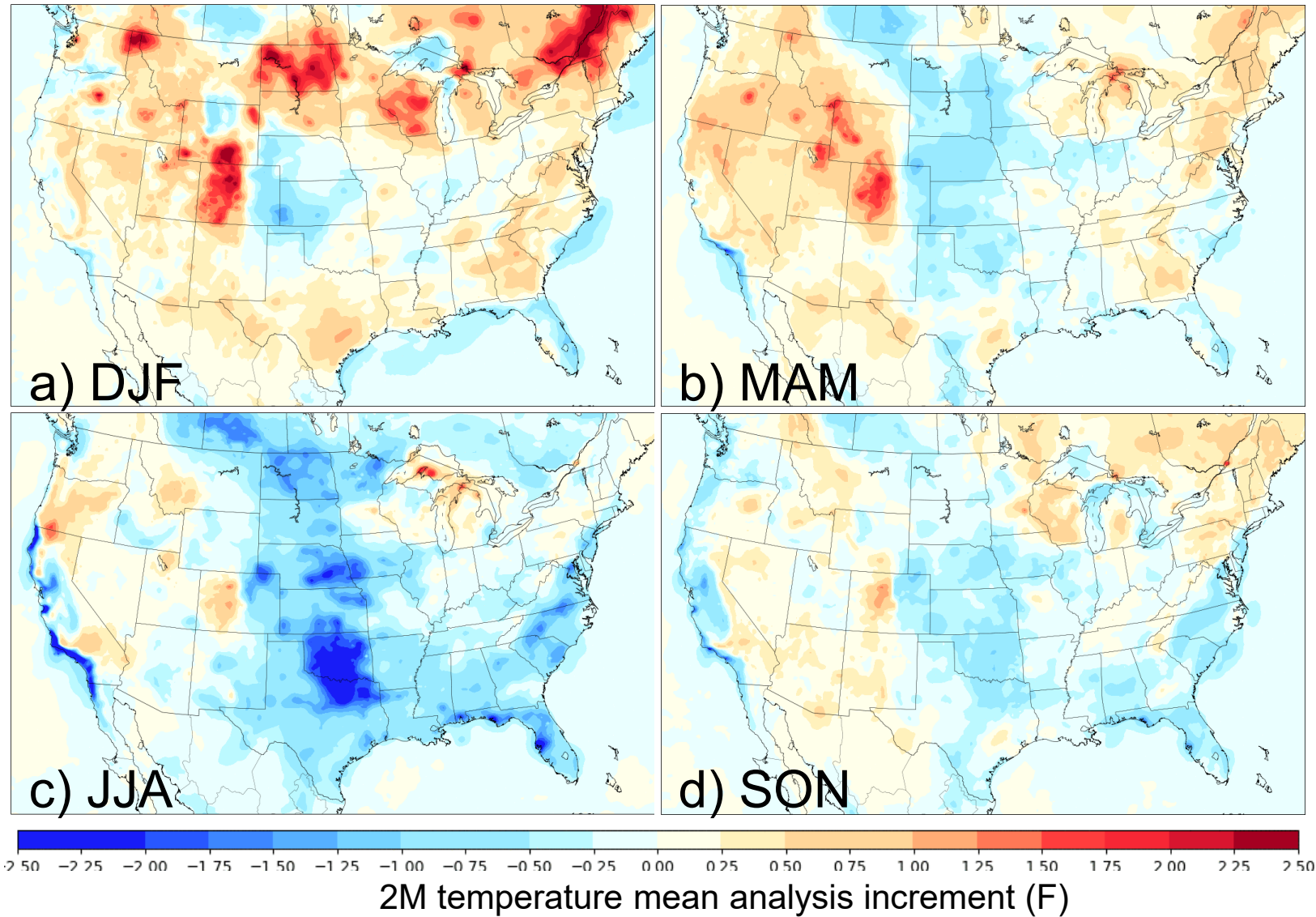


Radiosonde zonal wind fit to prior analysis

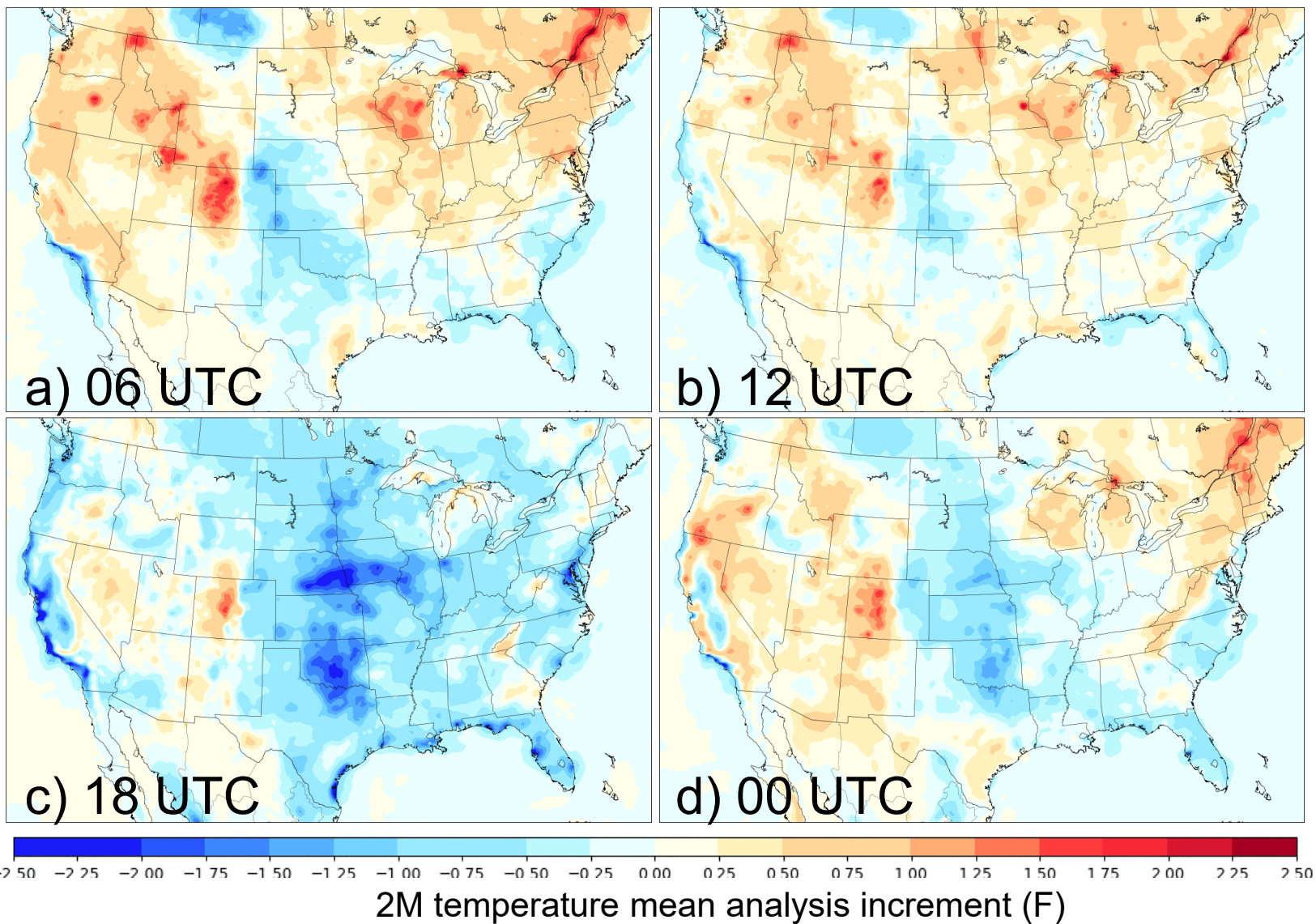


- NCAR ensemble physics configuration has less temperature bias
- Continuous cycling led to degraded analyses and poor forecast quality

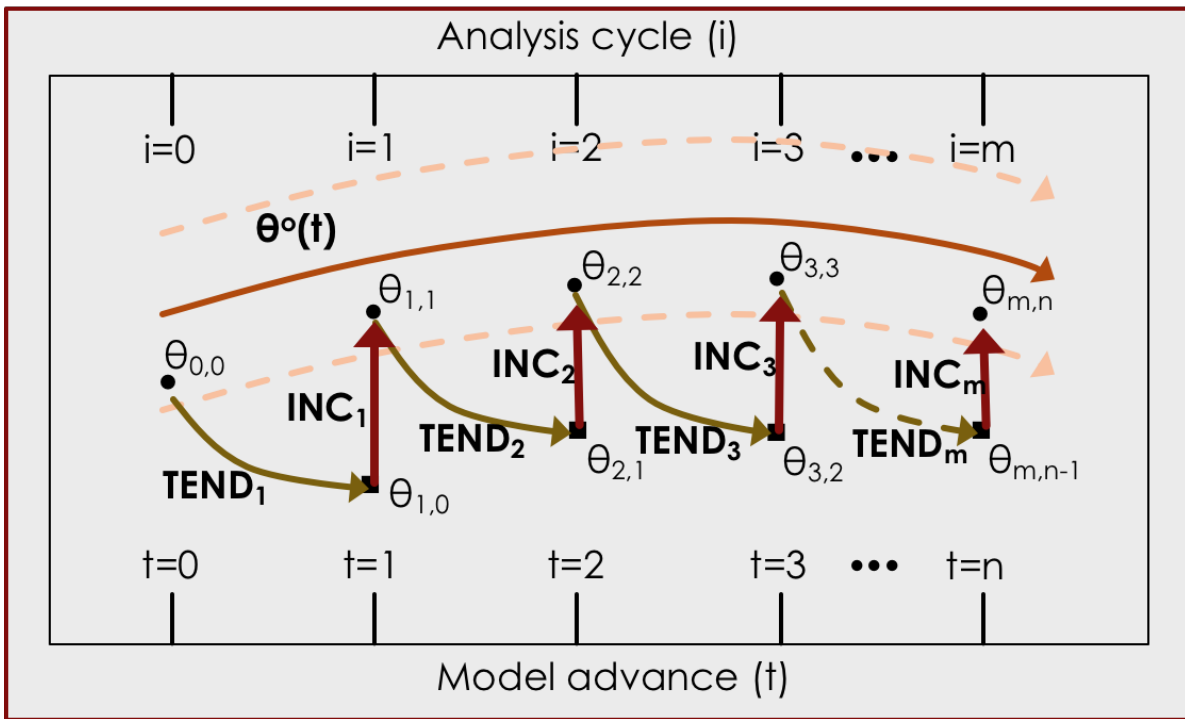
Seasonal variability in analysis increments



Diurnal variability in analysis increments



Time averaged physics tendencies to diagnose model error



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

Dynamics

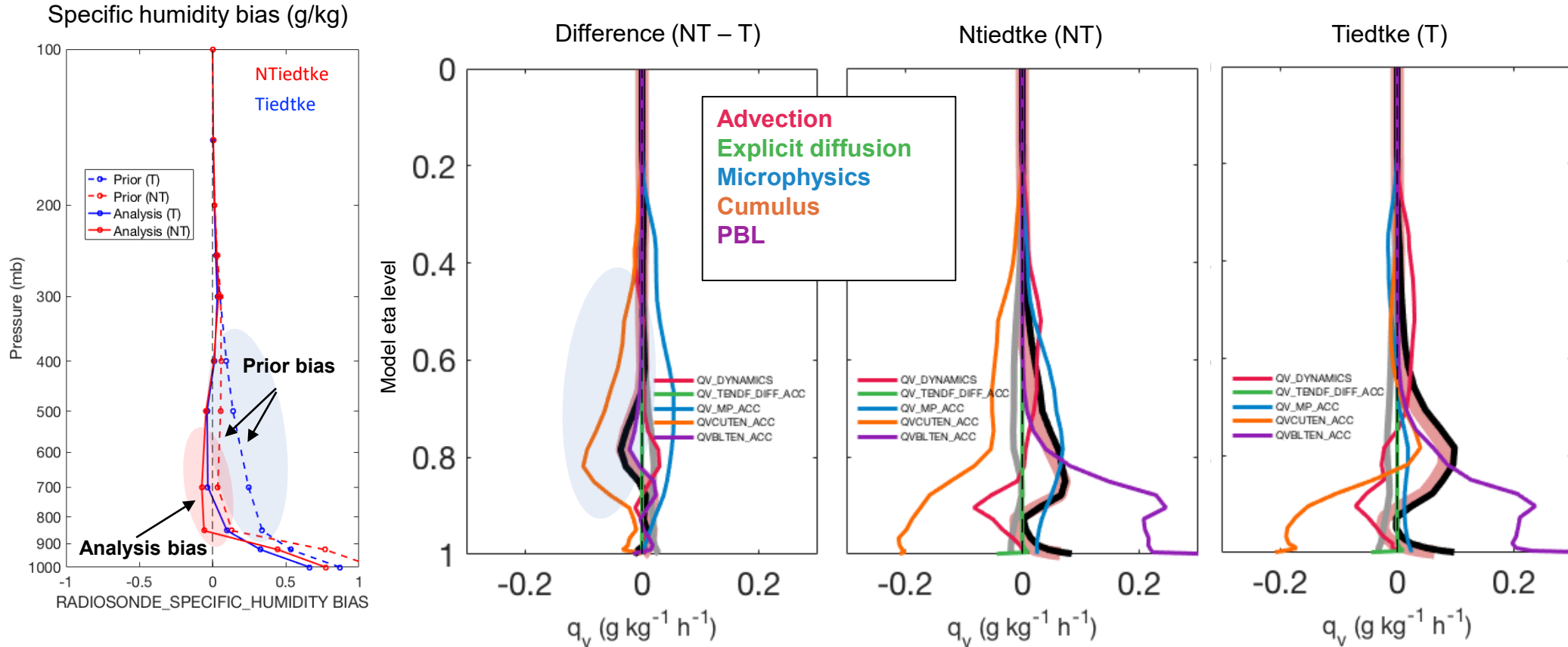
Physics

$\frac{\partial u}{\partial t} =$	Large time-step dynamics	+	Acoustic time-step dynamics due to	+	Explicit horizontal diffusion
	• Advection		• Gravity waves		+ PBL
$\frac{\partial v}{\partial t} =$	• Coriolis		• Acoustic waves		
	• PGF				
$\frac{\partial \theta}{\partial t} =$	Large time-step dynamics	+	Acoustic time-step dynamics due to	+	Explicit horizontal diffusion
	• Advection		• Gravity waves		+ PBL
			• Acoustic waves		+ Radiation
					+ Microphysics
$\frac{\partial q_v}{\partial t} =$	Large time-step dynamics			+	Explicit horizontal diffusion
	• Advection				+ PBL
					+ Microphysics

Averaged analysis increments balanced by model tendencies, which can be disaggregated to reveal sources of model error (See Rodwell and Palmer 2007; Cavallo et al. 2016; Rodwell et al. 2018)

Model bias test case: Updated cumulus scheme version

Model water vapor mixing ratio budgets

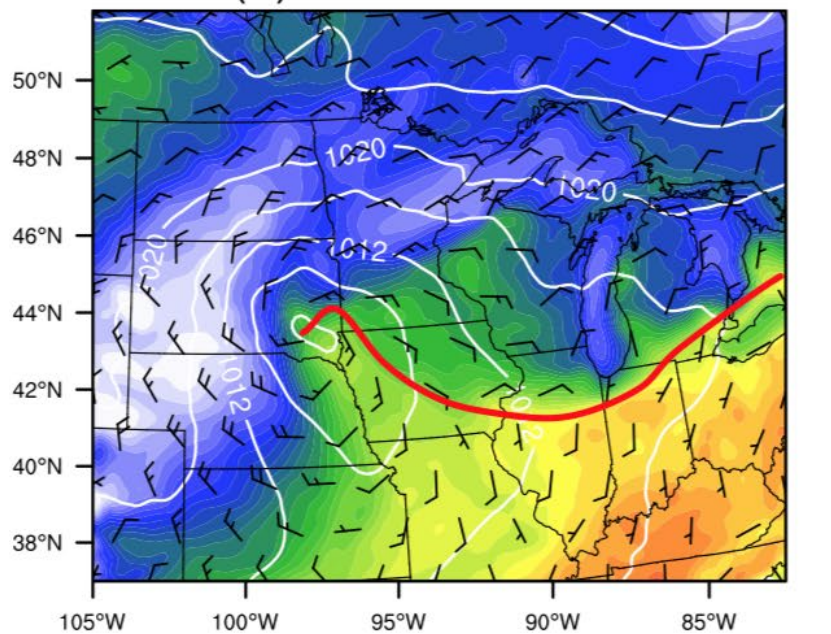


From M. Wong

Forecasts initialized with updated cumulus scheme have slower spinup of precipitation. Source of slower spinup tied to mean moisture analysis. The cumulus scheme, with interactions with the microphysics, are likely driving the differences we see in the q_v analysis state.

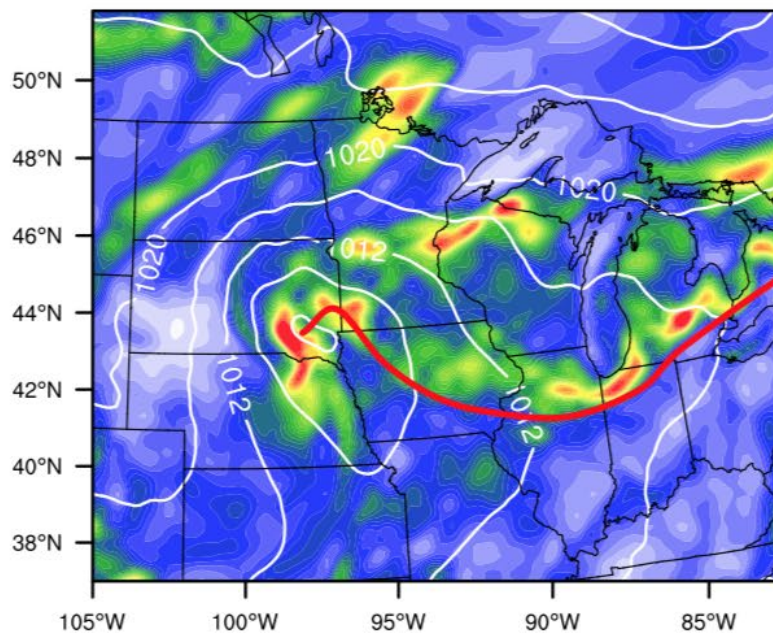
Ensemble spread – flow dependence

(b) Ensemble mean



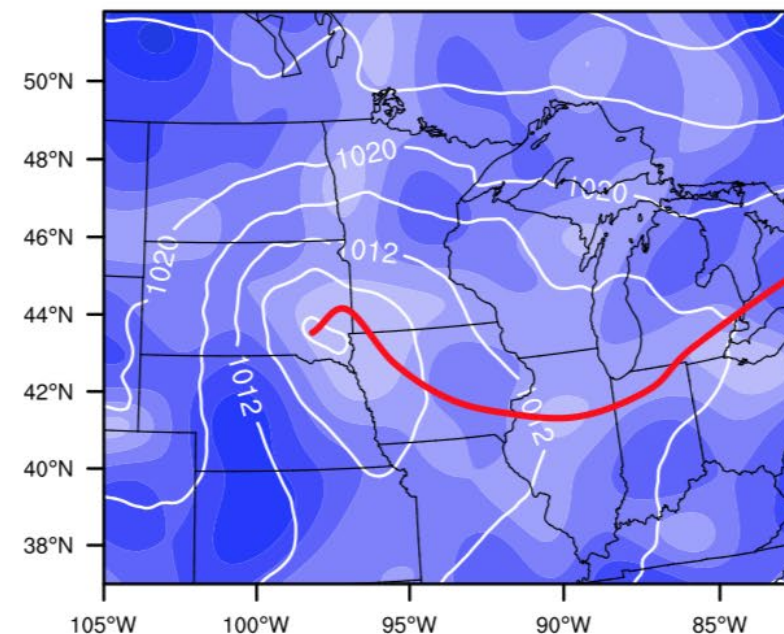
Ensemble mean temperature (°C)

(c) Flow-dependent ensemble standard deviation

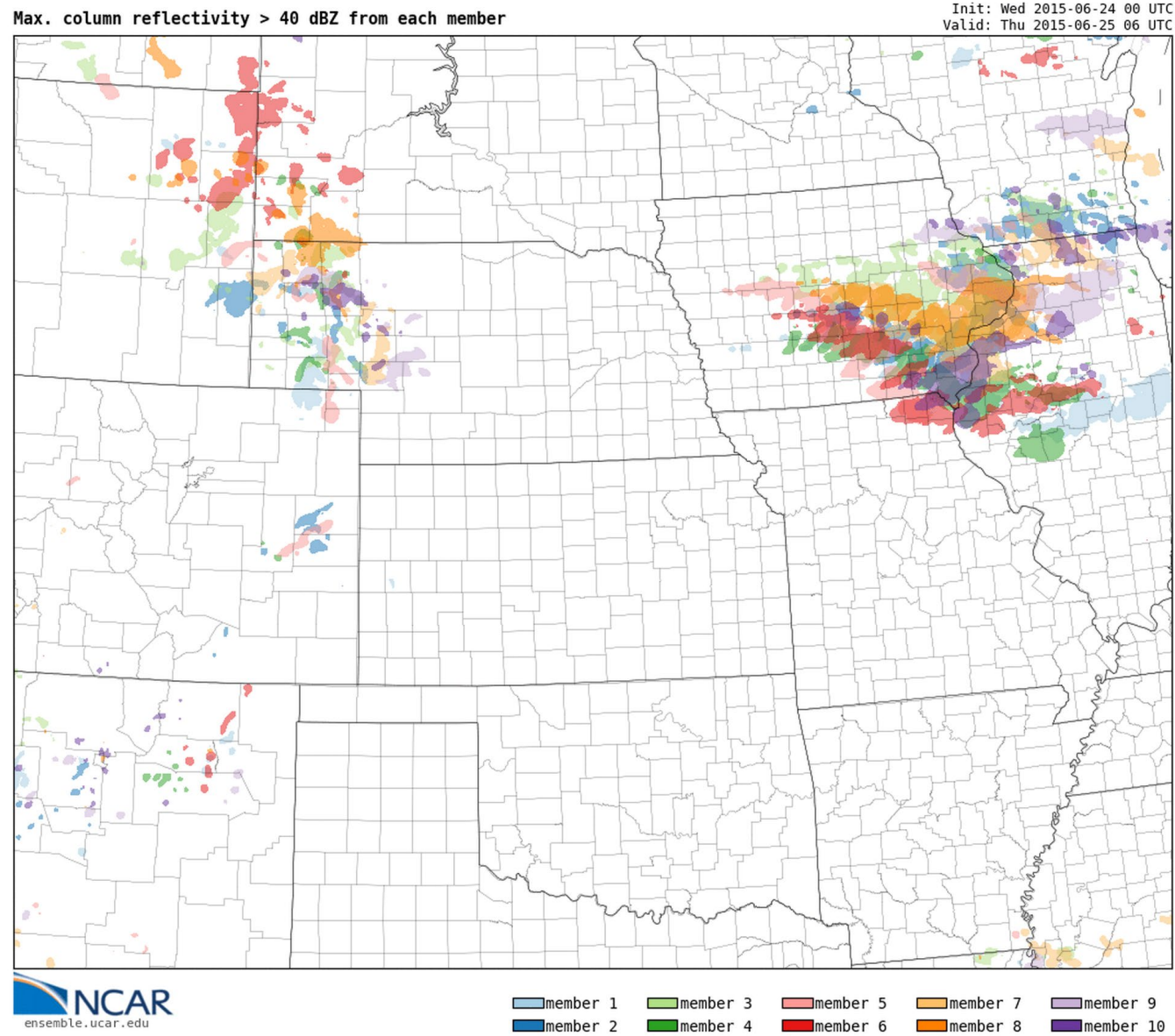


Temperature standard deviation (°C)

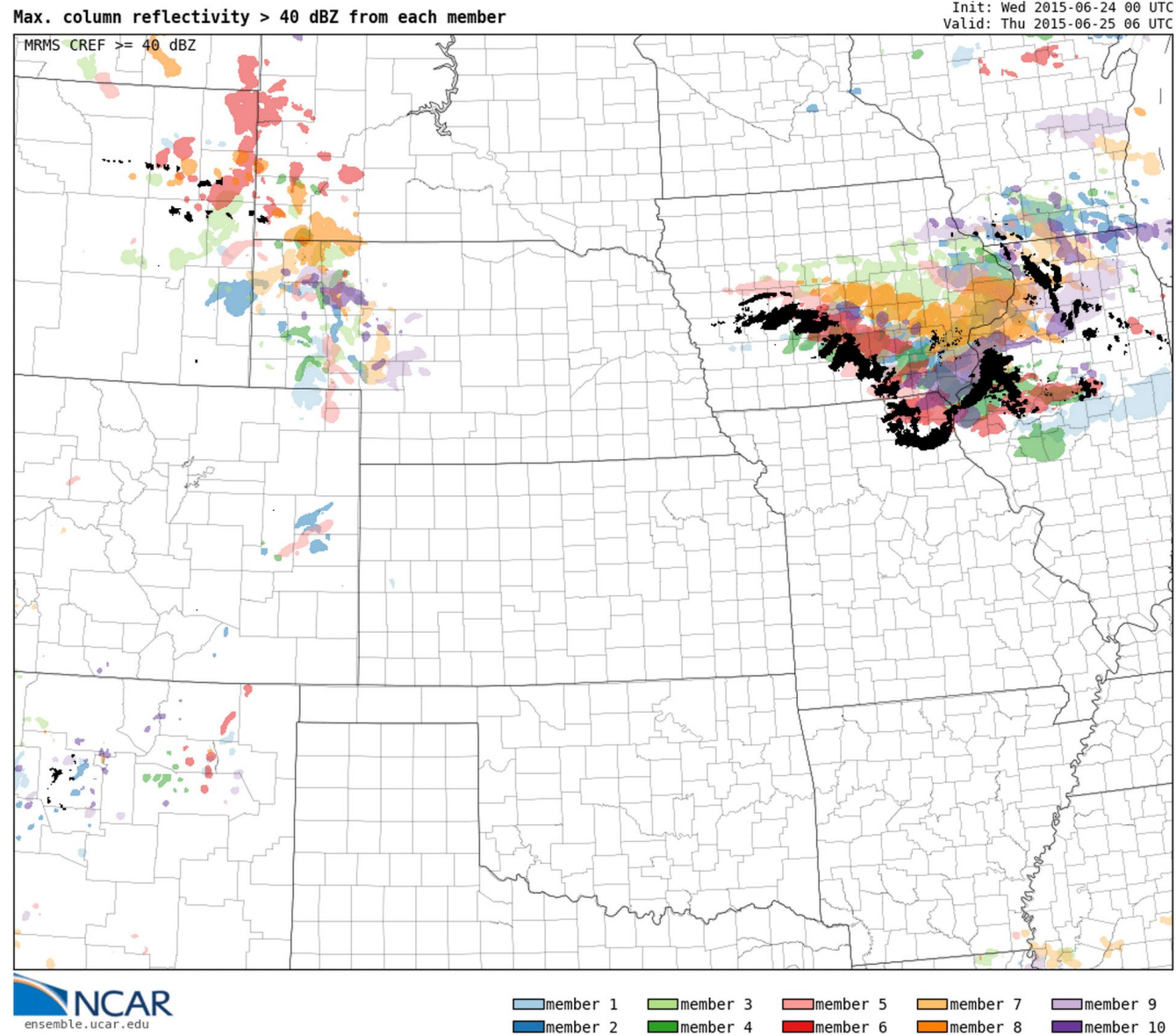
(d) Randomly-produced ensemble standard deviation



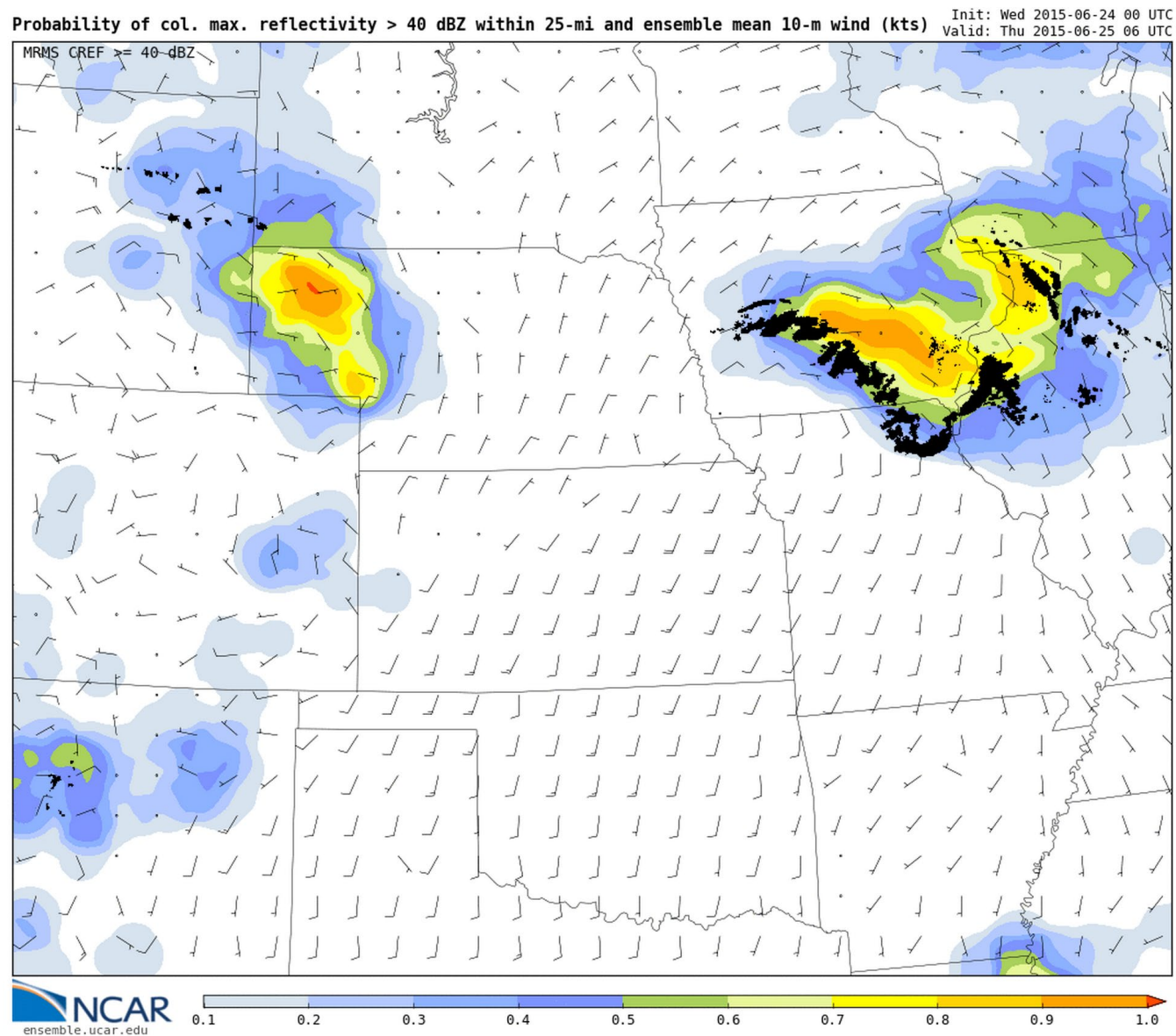
Verification - Ensemble spread – Paintball (spaghetti)



Verification - Ensemble spread – Paintball (spaghetti)

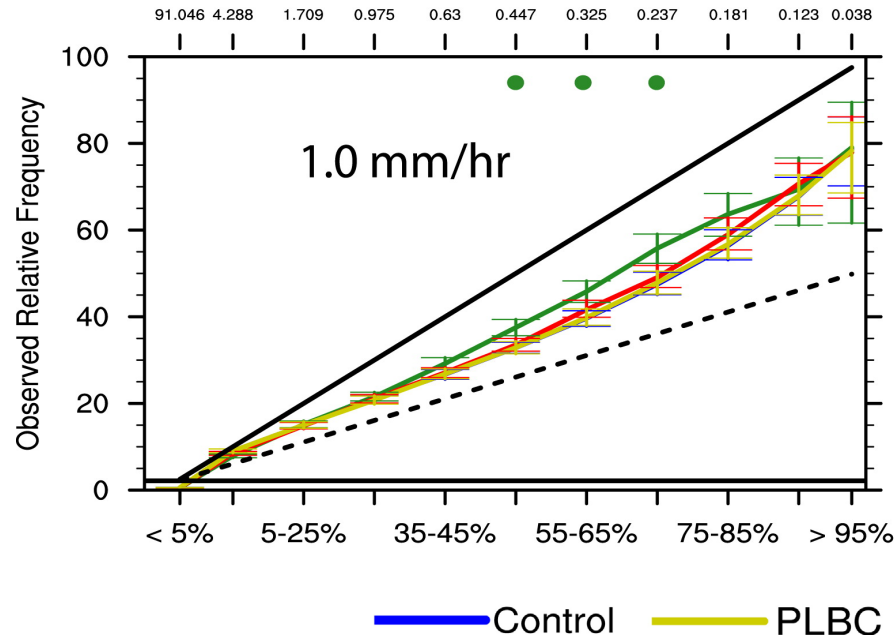


Verification - Ensemble spread – Neighborhood Probability

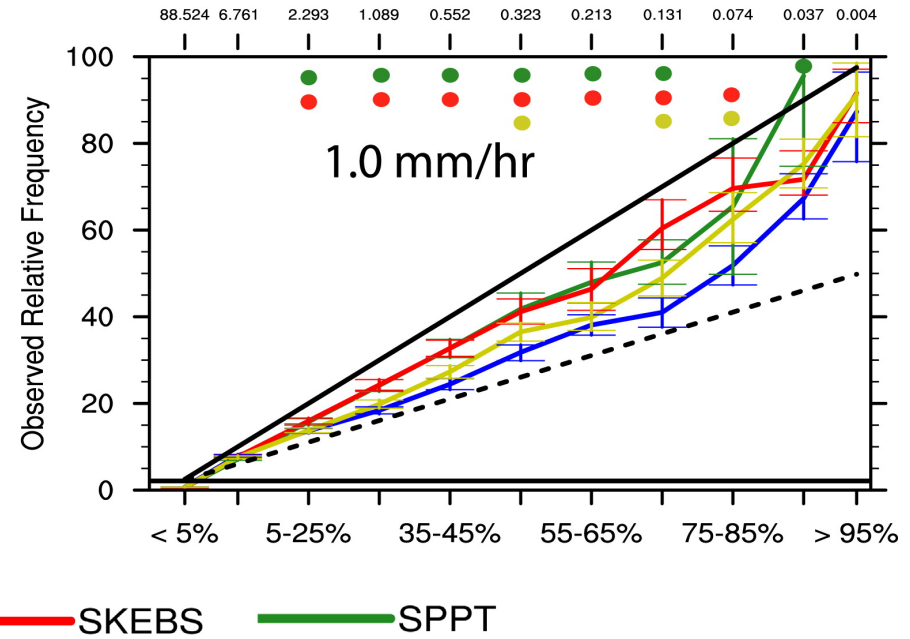


Cannot assess the value of a probability forecast from a single event!

Verification - Ensemble reliability – stochastic methods



Fhr 0-12

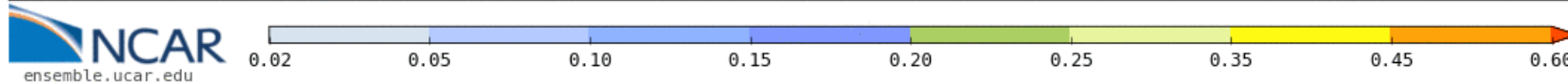
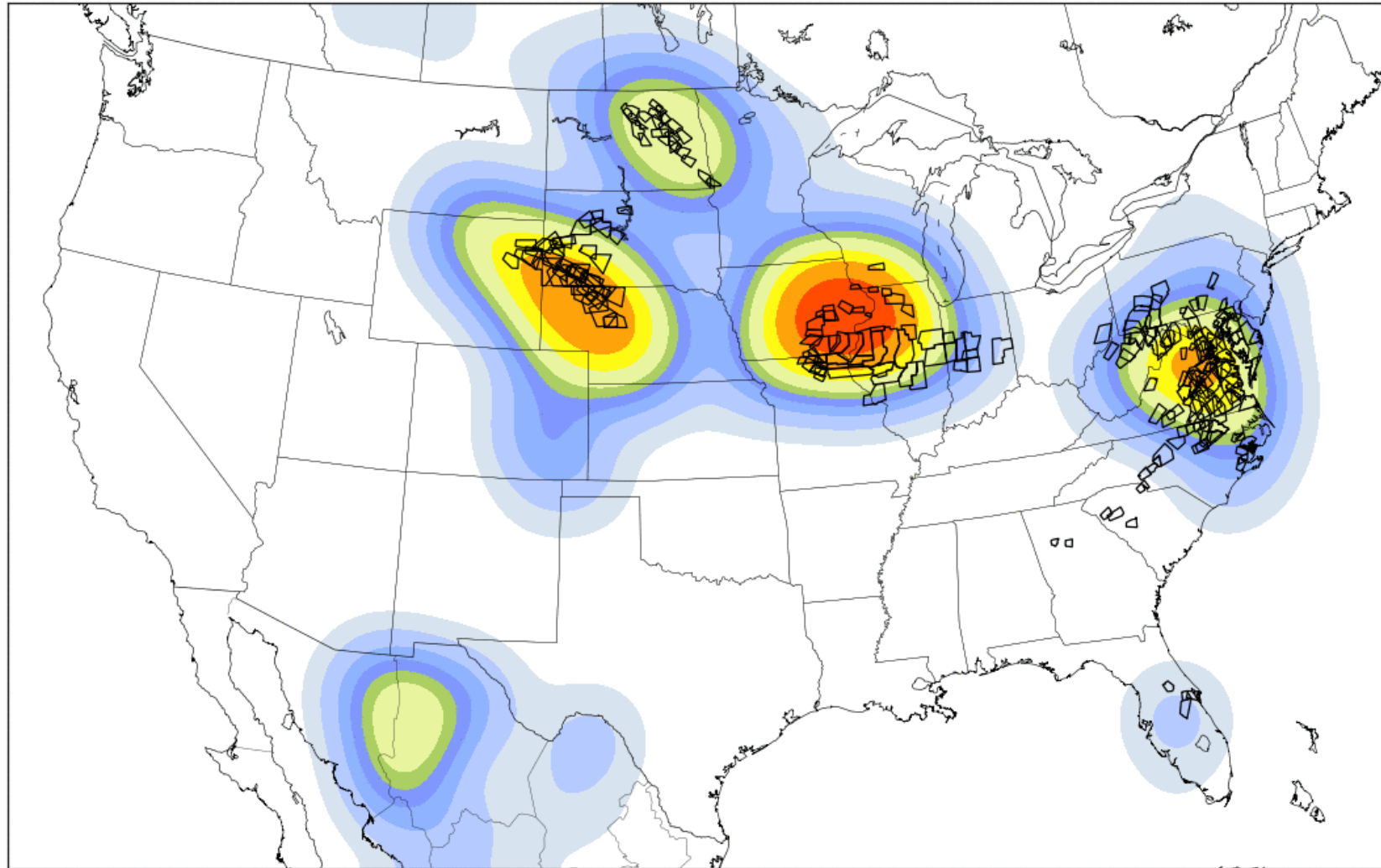


Fhr 18-36

Stochastic methods can improve reliability in longer range storm-scale forecasts, but less so in short-range (< 12 h) prediction (Romine et al. 2014)

Storm hazard verification

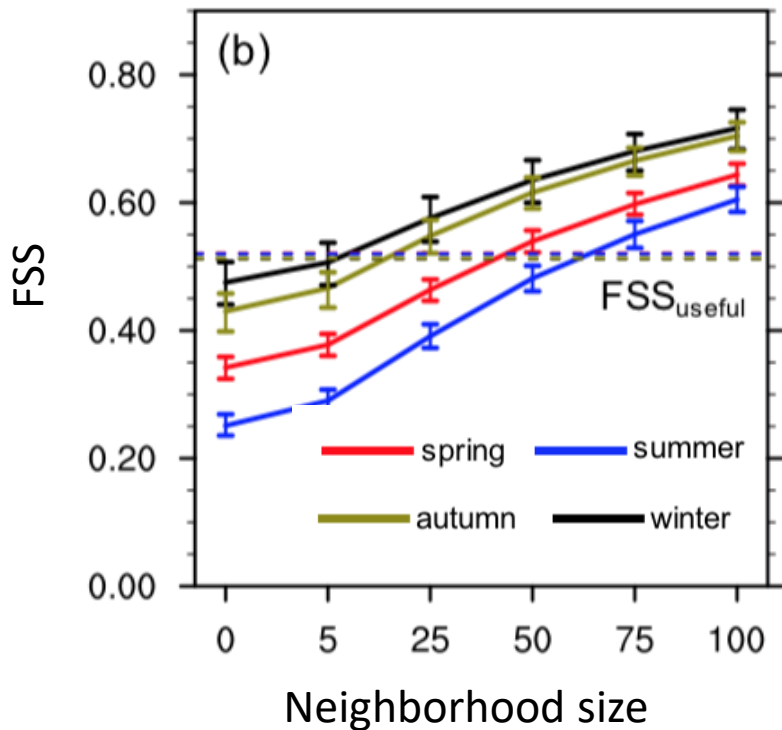
Day 1 prob. of UH > 75 m/s² or Wind > 22 ms⁻¹ or Hail > 1 in w/ NWS warns Init: Sat 2015-06-20 00 UTC
Valid: Sat 2015-06-20 12 UTC - Sun 2015-06-21 12 UTC



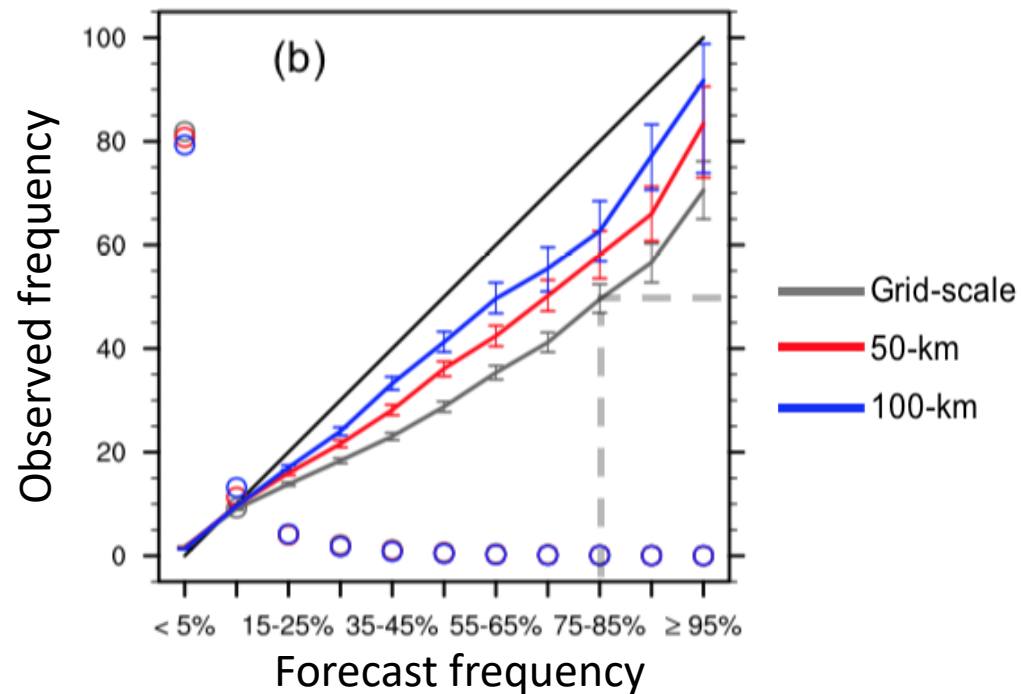
NWS warning polygons overlay on daily severe storm surrogate probabilities

Predictability Workshop - Norman, Ok

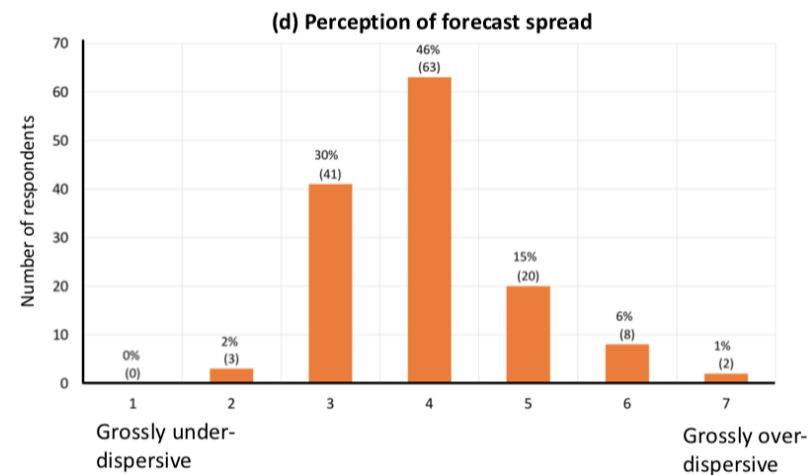
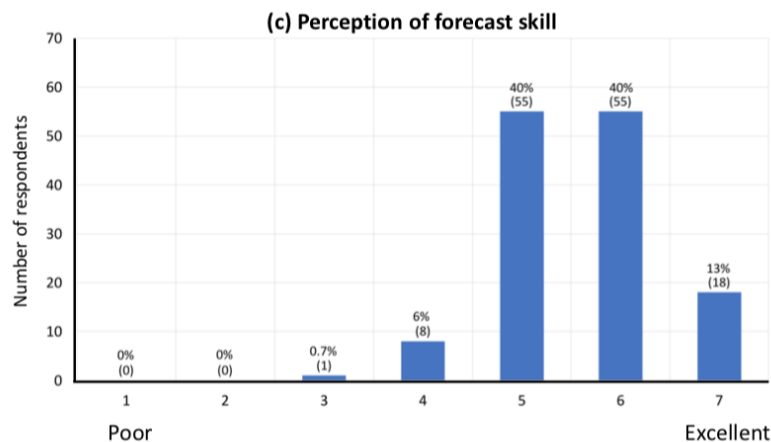
Skill/Reliability of NCAR ensemble precip forecasts



1 mm/hr



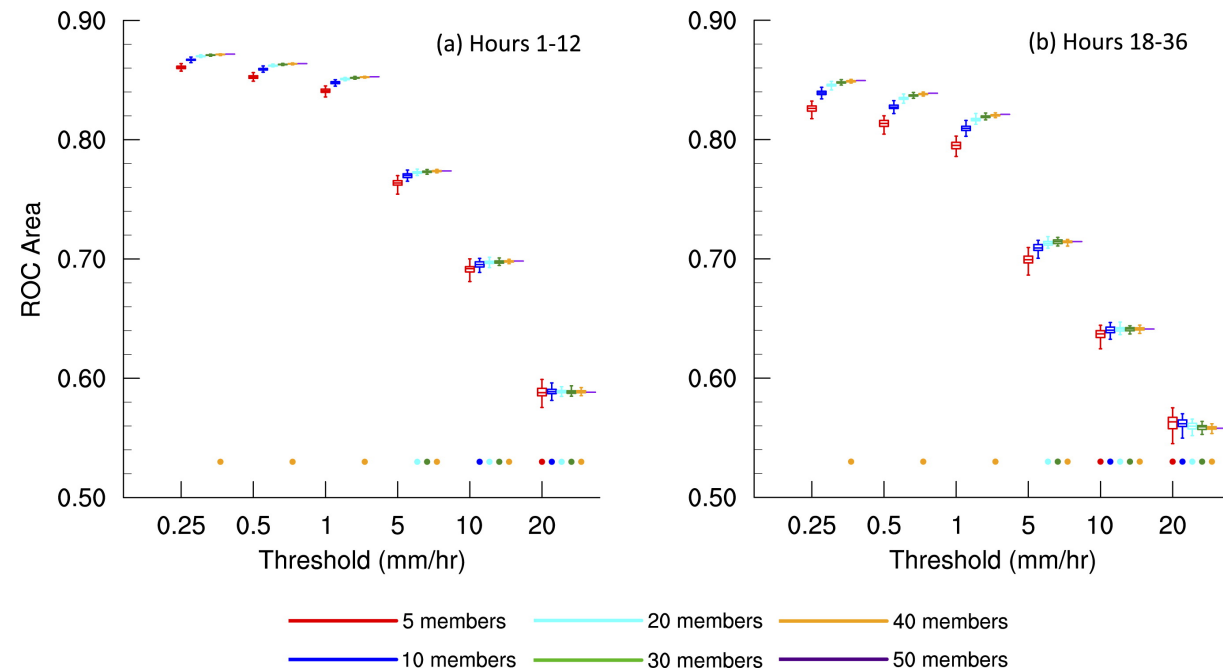
NCAR ensemble had similar skill to HREF, less reliable, but users felt quite good about the provided dispersion



See Schwartz et al. 2019

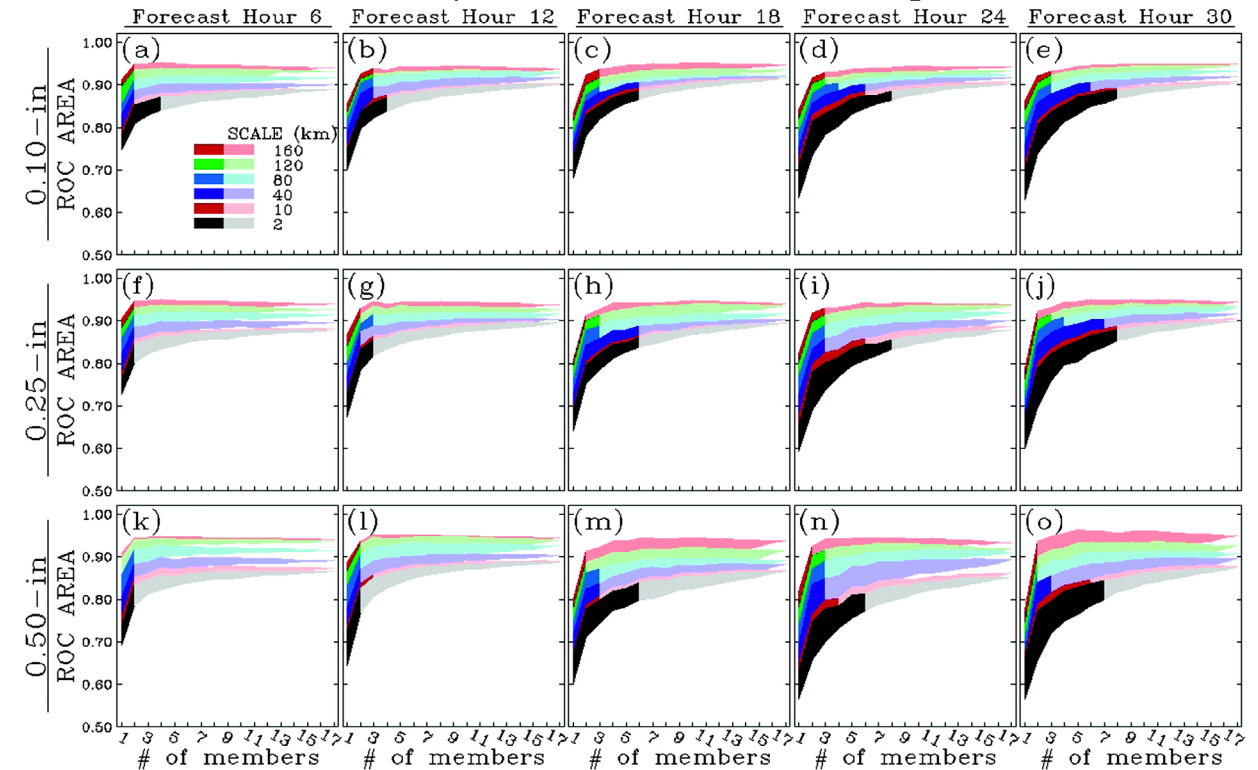
How many members are needed in a CAM ensemble?

single-physics EnKF initialized



Multi-physics CAPS runs

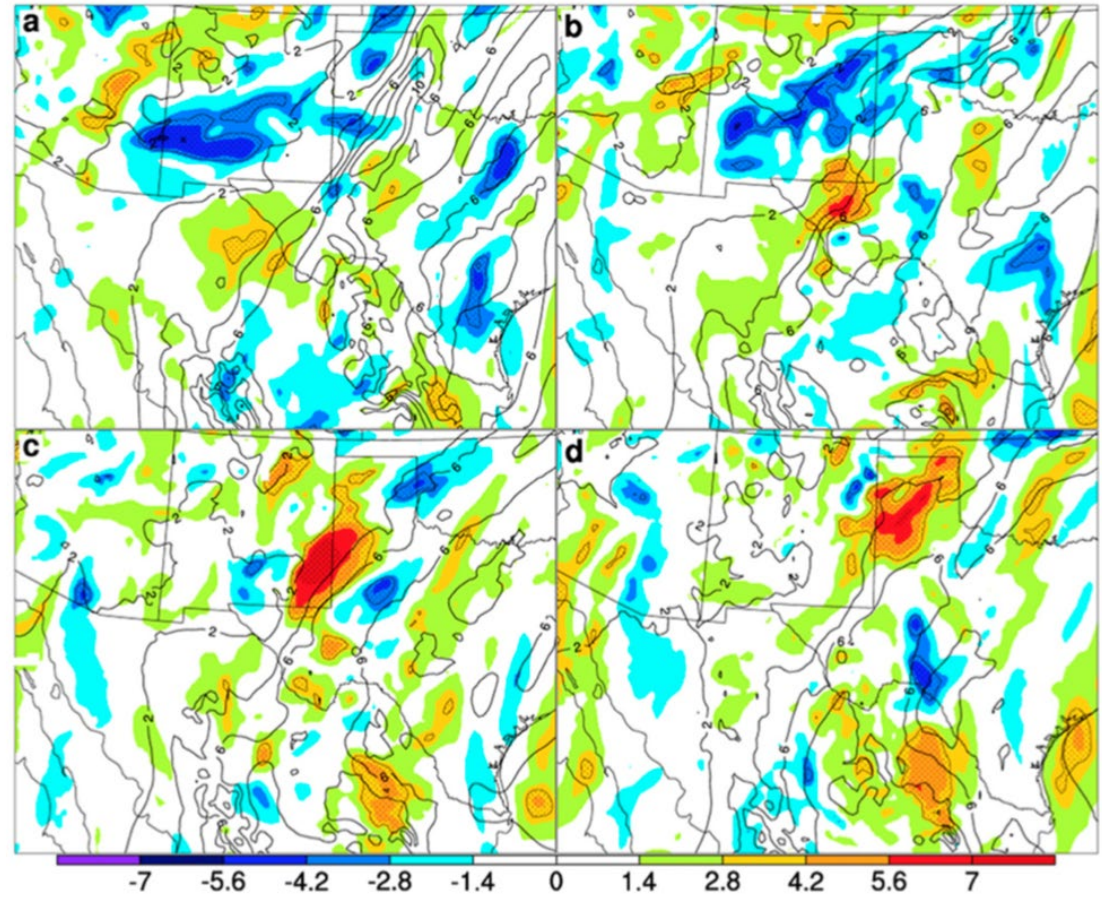
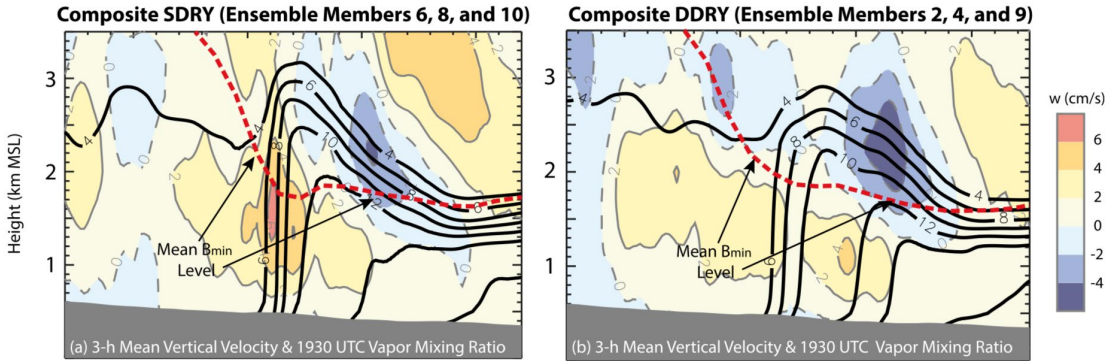
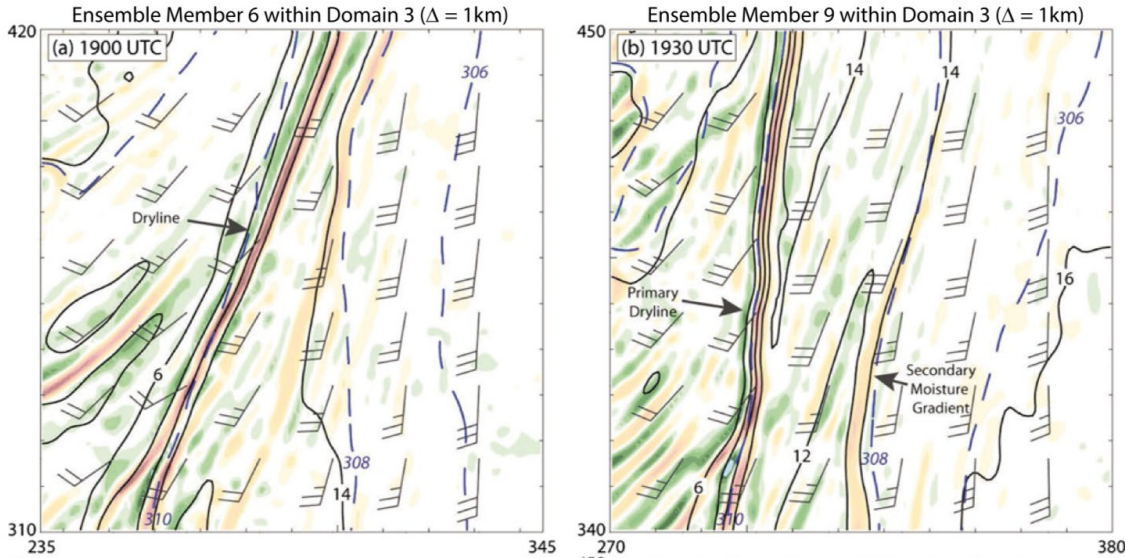
6-hrly Accumulated Precip



About ten or so members seems adequate to capture most of the degrees of freedom

Left – Schwartz et al. 2014; Right – Clark et al. 2011

Examples of CAM ensembles in physical process studies



Ensemble sensitivity analysis

$$\frac{\partial J}{\partial x_i} = \frac{\text{cov}(\mathbf{J}, \mathbf{x}_i)}{\text{var}(\mathbf{x}_i)}$$

Trier et al. 2015 (left); Torn et al. 2017 (right)

CAM ensemble summary

Positive contributions to CAM ensembles:

- Skillful model climate (essential in continuous cycling)
- Ensemble DA to generate flow-dependent ICs
- 10 members appears adequate for next-day prediction

Not so hot:

- Multi-X for investigation of systematic model errors and error growth characteristics – push toward model unification is ongoing

Some areas ripe for work:

- Distilling high-resolution CAM guidance
- Best practice CAM ensemble design
- Forecast model performance
- Capabilities to improve model performance in a systematic way
- Verification of CAM ensembles – lack adequate observations to observe processes