





Storm-scale ensemble design: Model error representation with WRF-ARW for severe storm prediction

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Severe storm prediction challenges

Confluence of:

- moisture
- instability
- lift mechanism
- sufficient shear

Key questions:

Where and when will convection occur, if at all?

How intense will convection be?

What will be the convective mode (primary hazards)?



Ensemble forecast system framing

Assumptions:

Ensemble – want <u>probabilistic</u>, not deterministic predictions High-resolution forecast (3 km grid spacing, explicit microphysics) Computational constraint - **regional model** (e.g., WRF) Ensemble DA for initial conditions (DART)

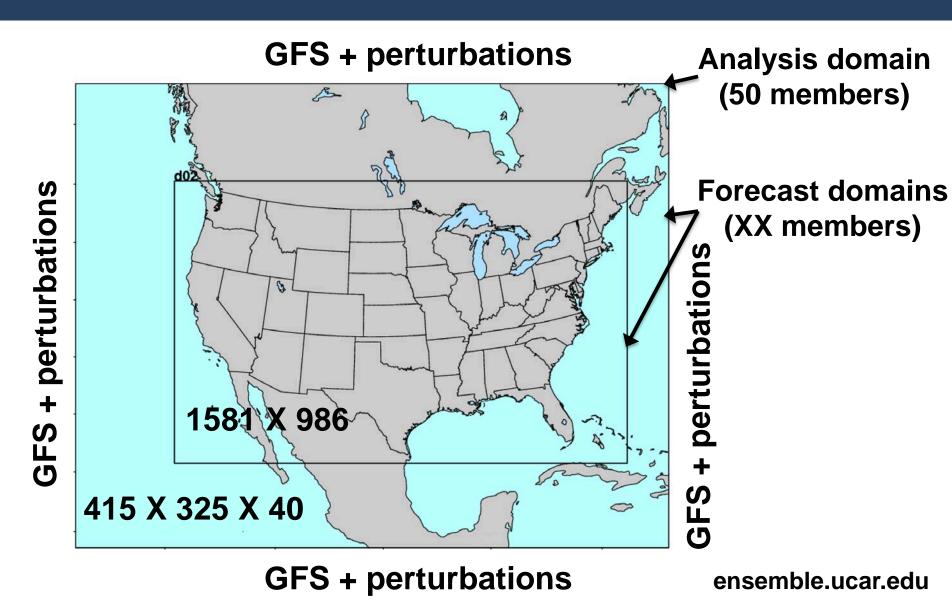
Basic elements of storm-scale ensemble forecast system design:

Initial condition uncertainty (e.g., ensemble DA) Lateral boundary condition uncertainty

Model error representation – notoriously under dispersive!



Example: NCAR Regional ensemble components



NCAR

Ensemble model error representation

<u>None</u>

Rely on lateral boundary perturbations and initial condition diversity

Multi-model/multi-physics/multi-parameter

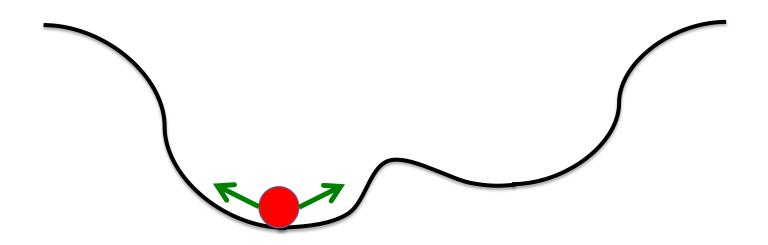
- Uncertain representations of physical processes
- Ensemble members may have varying skill and biases
- May be challenging to post-process (e.g. grids, variables, state size)

Stochastic methods

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



Stochastic schemes – theoretical framework



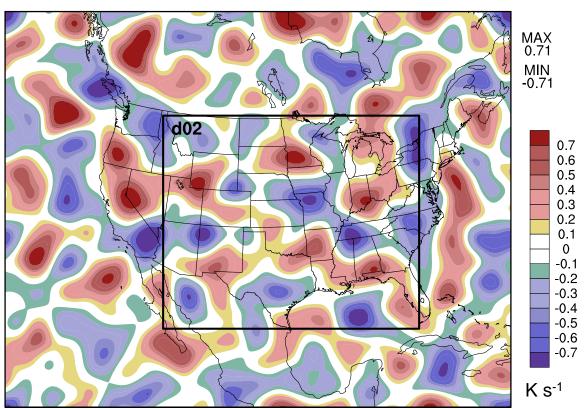
SKEBS – accounts for missing upscale energy cascade

SPPT – uncertain parameters within physics – project uncertainty in tendencies from packages (unconstrained)



Stochastic schemes – random forcing pattern

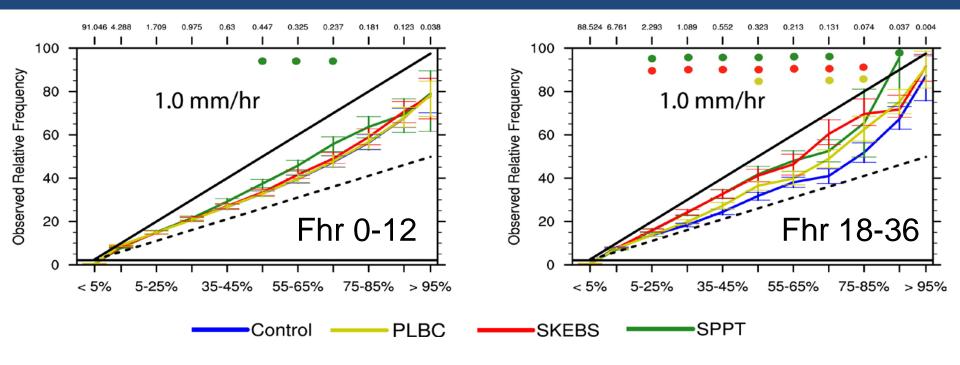




- Barotropic
- namelist options for spatial scales of pattern (wavenumber 1 -> 5 dx)
- Pattern can vary by winds/temperature forcing for SKEBS
- Decorrelation time scale same for all scales
- Same pattern used in SPPT tendency forcing



Ensemble reliability – precipitation



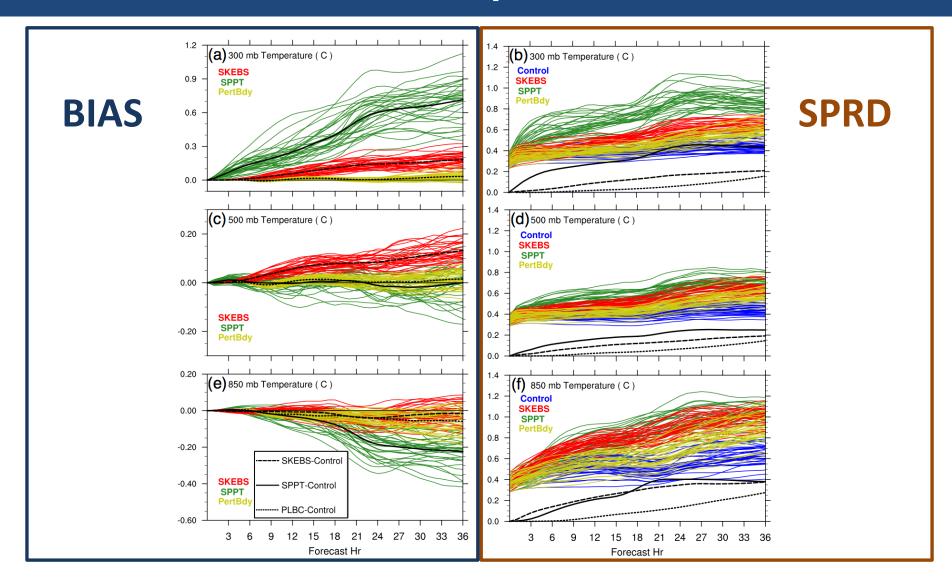
Attributes diagrams @ 1 mm h⁻¹ threshold

Overconfident predictions

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



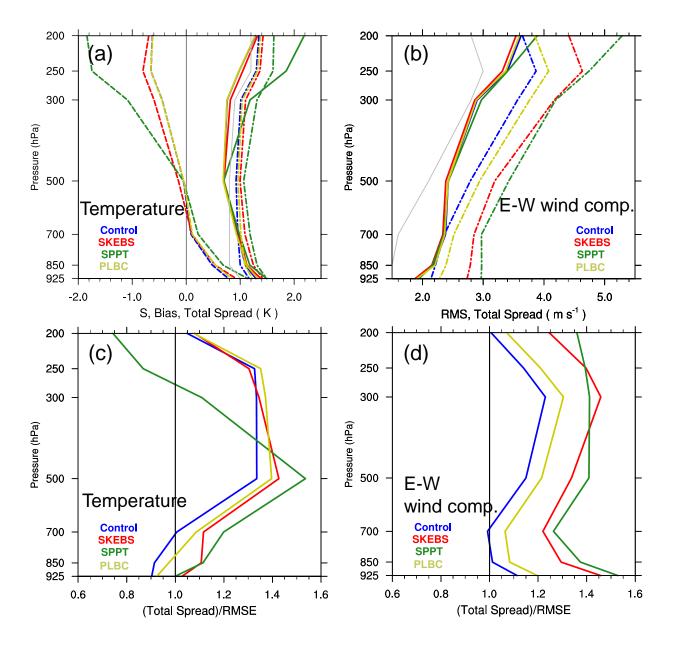
Forecast bias and spread time series



Bias drift from Control SPPT – largest bias drift, but also largest spread



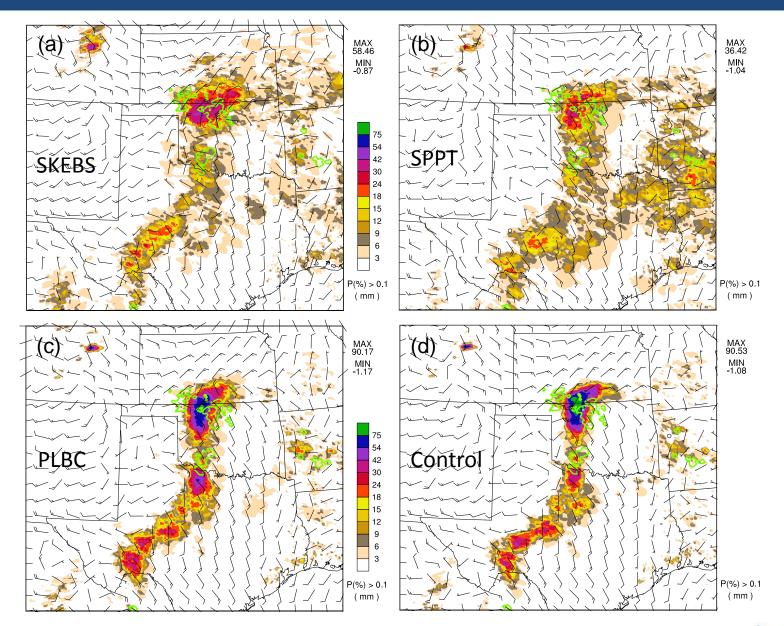
Fit to rawinsondes – dispersion test



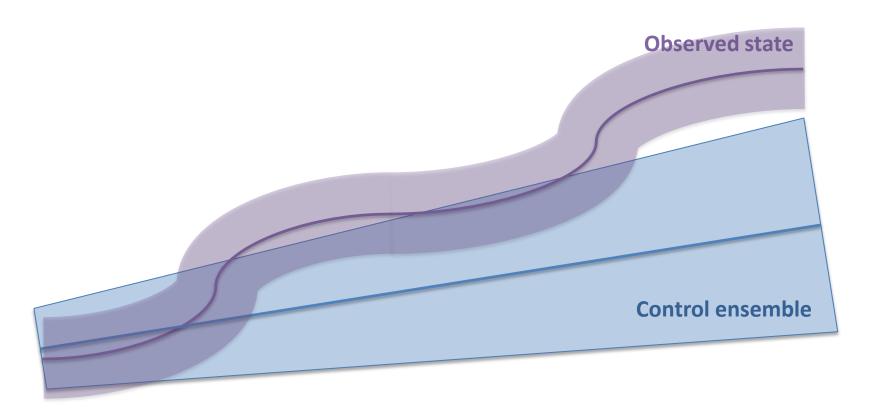
Verification against 24 h forecasts



Practical reliability for precipitation forecasts







Control ensemble:

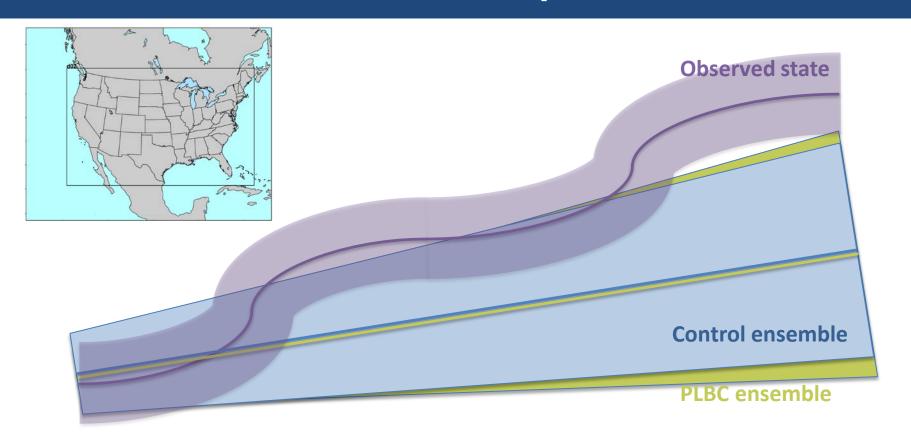
Estimates true evolution of the atmosphere

Lacks sufficient dispersion to capture the observed evolution after short integration

Select options:

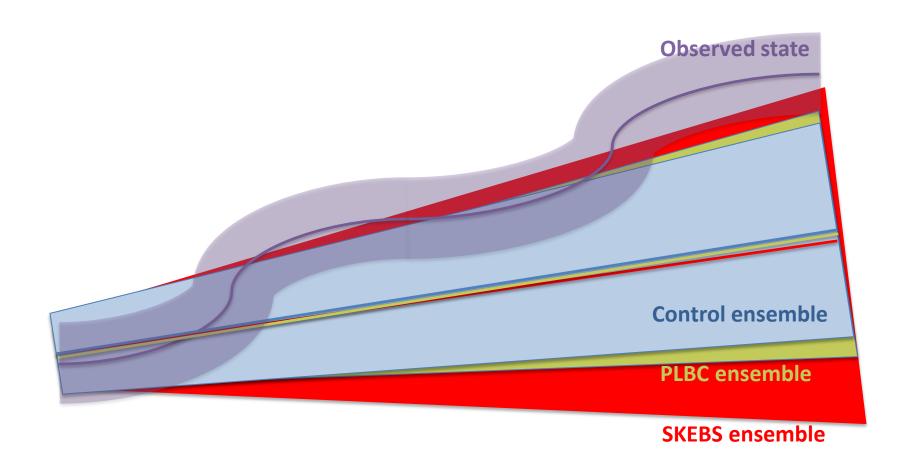
Multi-XXX, calibration, perturbed boundaries, stochastic methods





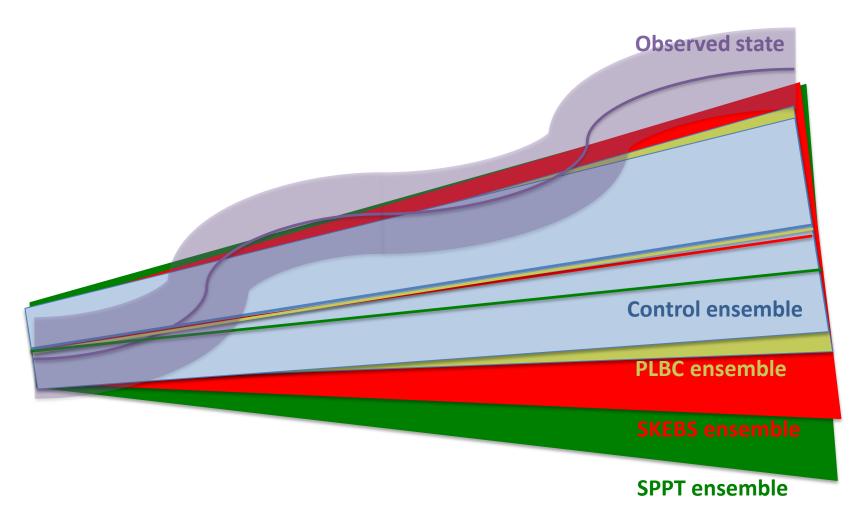
For NCAR ensemble, perturbing the lateral boundary condition improves spread somewhat, but late in the forecast. Ensemble mean is about the same.





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

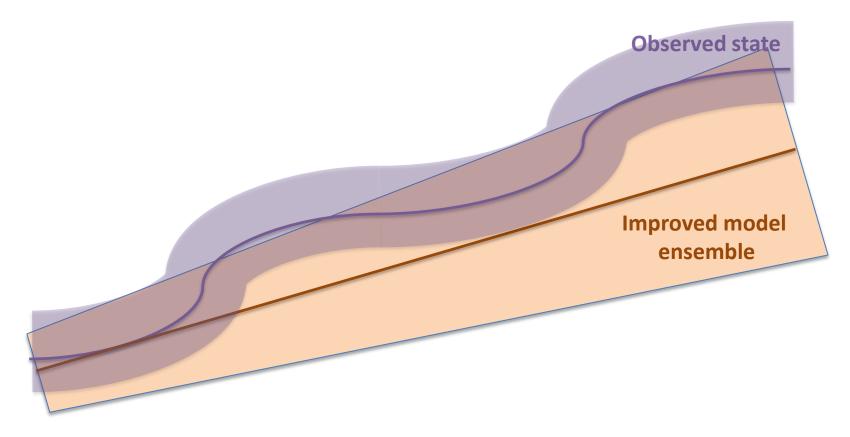




SPPT leads to even greater dispersion, beginning much earlier in the forecast, but the ensemble mean is further from the observed state relative to the control.



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

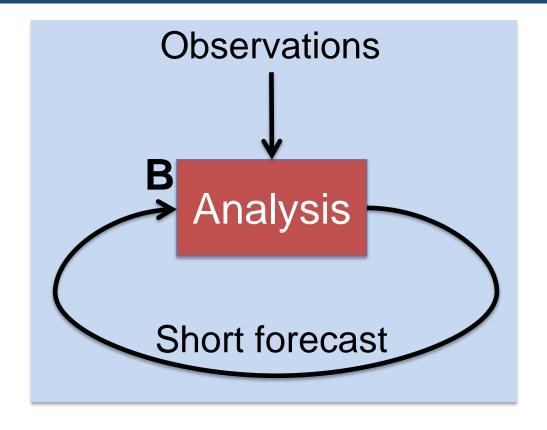


DA basics: continuously cycled analysis

Continuous cycling is 'best practice'

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

No 'spinup' needed, on the model attractor

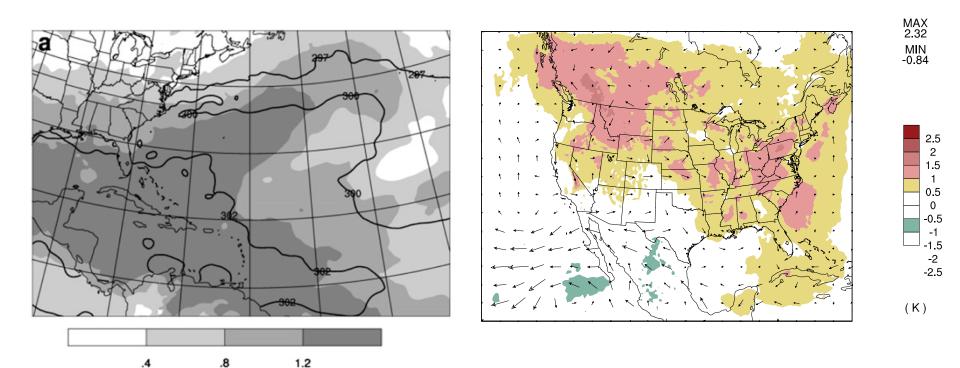


For regional models – nearly all centers use 'partial' cycling – periodically replacing the background from another (often global) analysis

Bad forecast model = degraded background for the analysis and forecasts (Torn and Davis 2013, Romine et al. 2013)



Continuous cycled DA – model error revealed



700 hPa 1-month average temperature bias

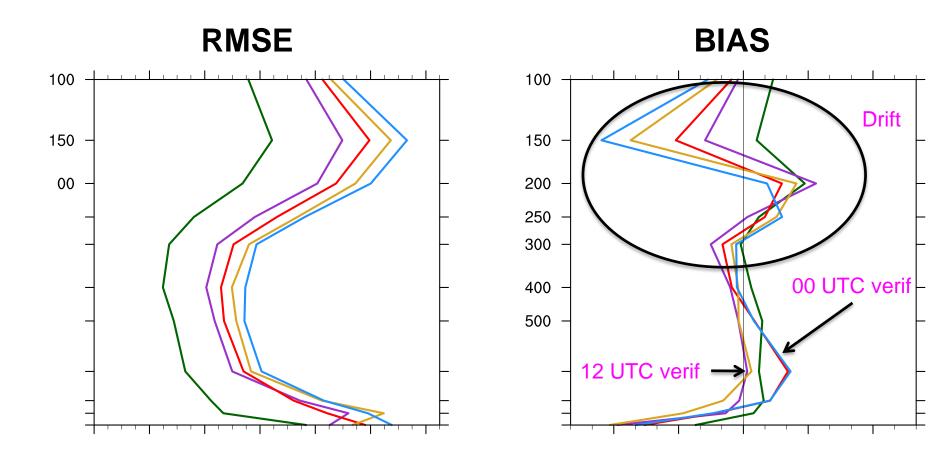
Torn and Davis (2012)

~ 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).



Verification challenges - rawinsondes

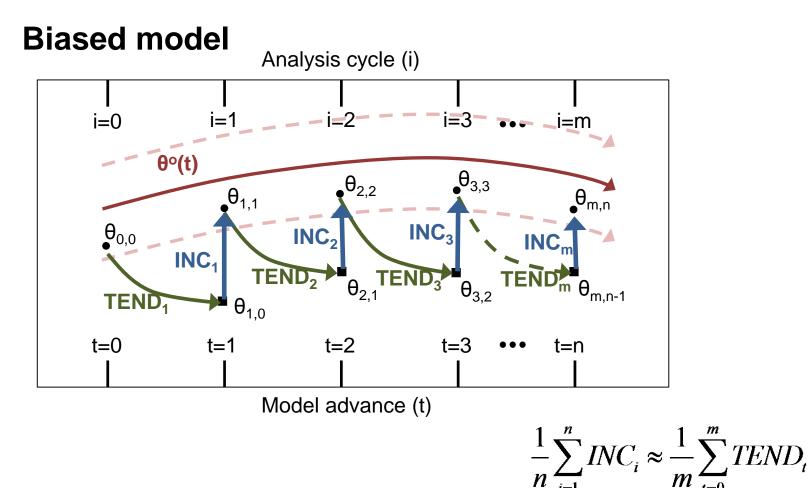


3-km ensemble forecast verification against rawinsondes 40 forecasts (late April to early June) Initial down-scaling, diurnal bias in mid- and lower-troposphere, drift near tropopause



Physics tendency tracking for model improvement

Future approach to model improvement?





Assessment of stochastic model error schemes

Convection-permitting ensemble forecasts for severe storm prediction

- addressing underdispersion in precipitation forecasts

Storm-scale ensemble design remains largely ad hoc

- here investigate stochastic methods to improve reliability

Stochastic schemes are found to:

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

Improving model physics possible through cycled DA:

Improve model climate toward observations/trusted analysis
Physics tendency methods may reveal sources of systematic error



NCAR regional ensemble ongoing research

Storm-scale ensemble design:

- Investigating initial perturbation roles in forecast performance
- Define 'physics suite' and try to improve through diagnostics
- Ensemble member grid spacing dependency
- Ensemble DA development

Drawing guidance from storm-scale ensembles:

- Discriminating severe weather hazards
- Probabilistic guidance for broader hazards (flooding, transportation, renewables, etc...)

