Model error representation in WRF/DART

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MMM/NCAR

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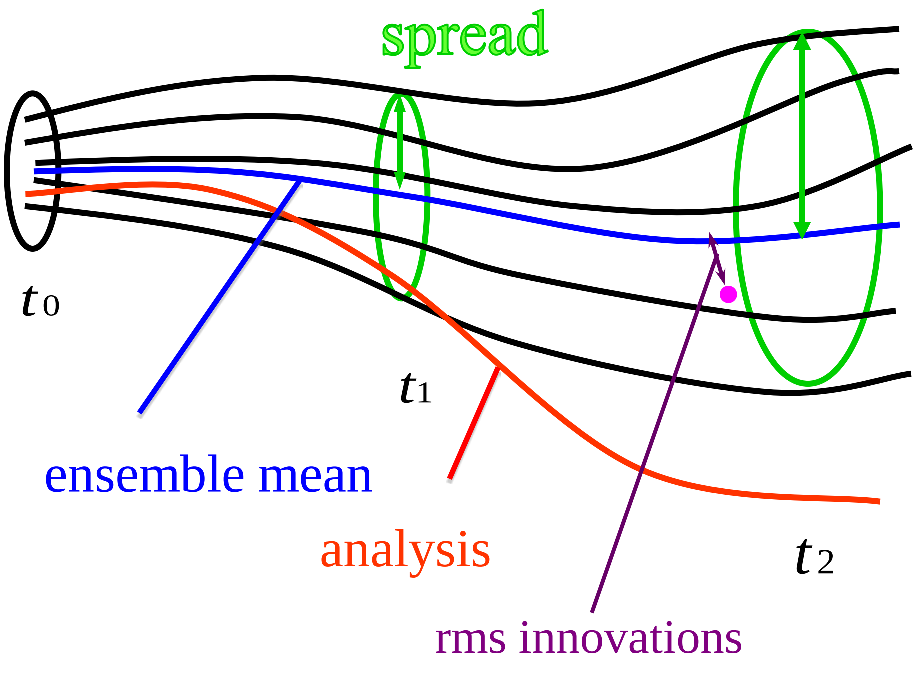
Why model uncertainty representations

- ✓ All current operational ensemble systems are **underdispersive**; The rms error grows faster than the spread.
  => the best estimate of the true atmospheric state is on average more often outside the range of predicted states than statistically expected. (Buizza et al. 2005)
- ✓ Small uncertainties in the initial state and NWP model lead to forecast errors and flow-dependent predictability.



Model uncertainties in short-range weather prediction

- ✓ Forecast error = IC error + Model error + LBC error
- ✓ Model errors represented by multi-model, multi-physics, multi-parameter, and stochastic schemes
- ✓ Retrospective case studies using the AFWA's mesoscale ensemble prediction system (Hacker et al. 2011; Berner et al. 2011) showed that

  ⇒ Including a model-error representation leads to ensemble systems that produce significantly better probabilistic forecasts than a control physics ensemble that uses the same physics schemes for all ensemble members.

  ⇒ In overall, the stochastic kinetic-energy backscatter scheme is comparable or superior to the multi-physics ensemble.

  ⇒ The best performing ensemble system is obtained by combining the multi-physics scheme with the stochastic kinetic-energy backscatter scheme.

Model uncertainties in WRF/DART cycling

- Control-physics (CP) ensemble: each ensemble member uses the same physics configuration, but ensemble prior spread is adaptively inflated based on the observation likelihood and the prior PDF right before the analysis step.
- Multi-physics (MP) ensemble: each ensemble member uses a different set of physics schemes.
- Stochastic kinetic-energy backscatter (BS) ensemble: each ensemble member is perturbed by a stochastic forcing term that represents the statistical fluctuations in the subgrid-scale fluxes.

Multi-Physics ensemble configuration

- AFWA's Mesoscale Ensemble Prediction System (MEPS)

Member (JME mem)	Physical parameterizations					
	Surface	Microphysics	PBL	Cumulus	LW_RA	SW_RA
1	Thermal	Kessler	YSU	KF	RRTM	Dudhia
2	Thermal	WSM6	MYJ	KF	RRTM	CAM
3	Noah	Kessler	MYJ	BM	CAM	Dudhia
4	Noah	Lin	MYJ	Grell	CAM	CAM
5	Noah	WSM5	YSU	KF	RRTM	Dudhia
6	Noah	WSM5	MYJ	Grell	RRTM	Dudhia
7	RUC	Lin	YSU	BM	CAM	Dudhia
8	RUC	Eta	MYJ	KF	RRTM	Dudhia
9	RUC	Eta	YSU	BM	RRTM	CAM
10	RUC	Thompson	MYJ	Grell	CAM	CAM

The Kalman Filter (KF)

Assume

- $\mathbf{x}^t \sim N(\overline{\mathbf{x}}^f, \mathbf{P}^f)$; Gaussian forecast errors
- $\epsilon \sim N(\mathbf{0}, \mathbf{R})$; Gaussian observation errors

KF analysis implements Bayes rule for Gaussians

- analysis equations:

$$\overline{\mathbf{x}}^a = \overline{\mathbf{x}}^f + \mathbf{K}(\mathbf{y} - \mathbf{H}\overline{\mathbf{x}}^f) \quad ; \quad \mathbf{P}^a = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}^f,$$

- Kalman gain

$$\mathbf{K} = \mathbf{P}^f\mathbf{H}^T(\mathbf{H}\mathbf{P}^f\mathbf{H}^T + \mathbf{R})^{-1}$$

Computationally difficult unless problem is small

- $\mathbf{P}^f$, $\mathbf{P}^a$ are $N_x \times N_x$, w/ $N_x = \dim \mathbf{x}$

Ensemble Kalman Filter (EnKF)

- EnKF analysis step
  - As in KF analysis step, but uses sample (ensemble) estimates for covariances => the huge matrix P^f is never explicitly computed.

$$\mathbf{P}^f\mathbf{H}^T = \frac{1}{N-1}\sum_{i=1}^{N}(\mathbf{x^f} - \overline{\mathbf{x^f}})(\mathbf{Hx^f} - \overline{\mathbf{Hx^f}})^\mathbf{T}$$

$$\mathbf{HP}^f\mathbf{H}^T = \frac{1}{N-1}\sum_{i=1}^{N}(\mathbf{Hx^f} - \overline{\mathbf{Hx^f}})(\mathbf{Hx^f} - \overline{\mathbf{Hx^f}})^\mathbf{T}$$

$$\textit{where}\ \ \overline{\mathbf{x^f}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{x^f}\quad \textit{and}\ \ \overline{\mathbf{Hx^f}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{Hx^f}$$

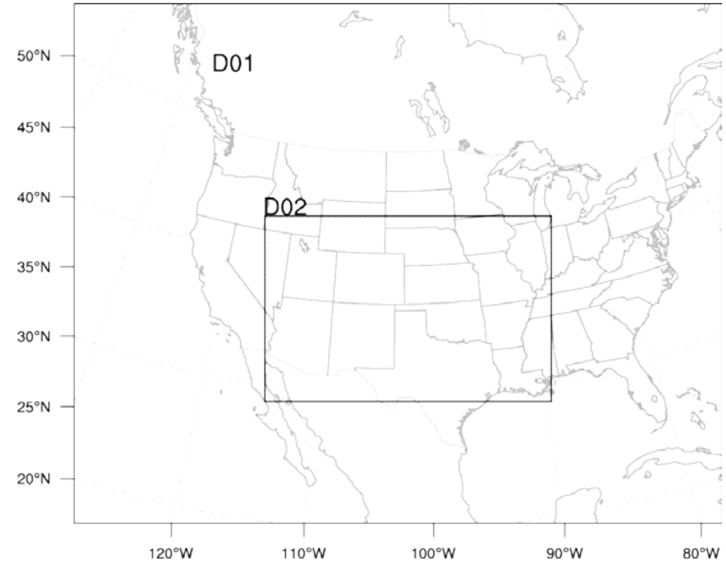
$y^f = \mathbf{H}\mathbf{x}^f$ is the forecast, or prior observation.

  - Output of EnKF analysis step is ensemble of analyses
- EnKF forecast step
  - Each member integrated forward with full nonlinear model to provide flow-dependent background error covariance
  - Monte-Carlo generalization of KF forecast step

Ensemble Kalman Filter (EnKF) in DART

- Data Assimilation Research Testbed (DART) is general software for ensemble filtering:
  - Assimilation scheme(s) are independent of model
  - Interfaces exist for numerous models: WRF (including global and single column), CAM (spectral and FV), others
  - See http://www.image.ucar.edu/DAReS/DART/

Experiment design



Grids

D1: 123 x 99 (45-km)

D2: 163 x 106 (15-km)

41 levels, two-way nesting

IC/LBCs

- 1°x1° GFS analyses were used for initialization in both domains
- 1°x1° GFS forecasts were used to generate lateral boundaries at 45-km grid four times a day

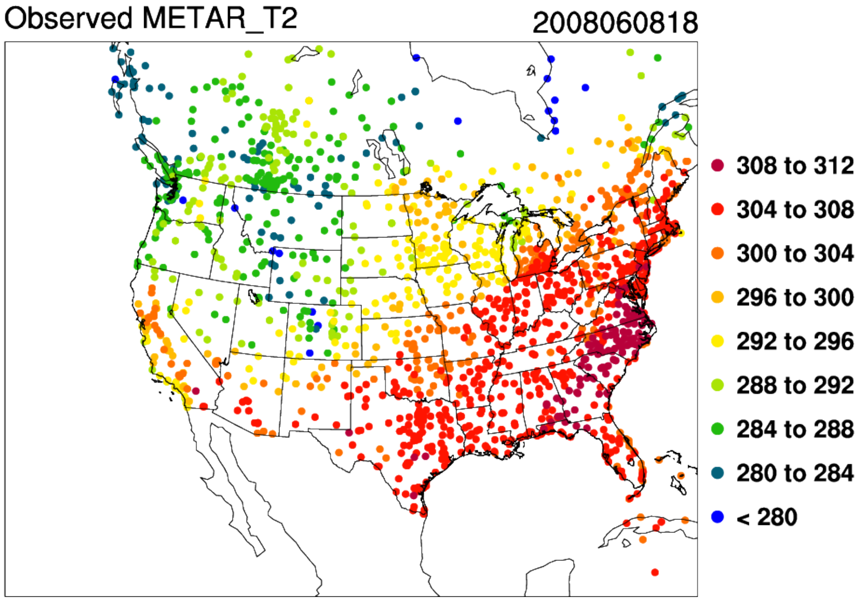
Ensemble

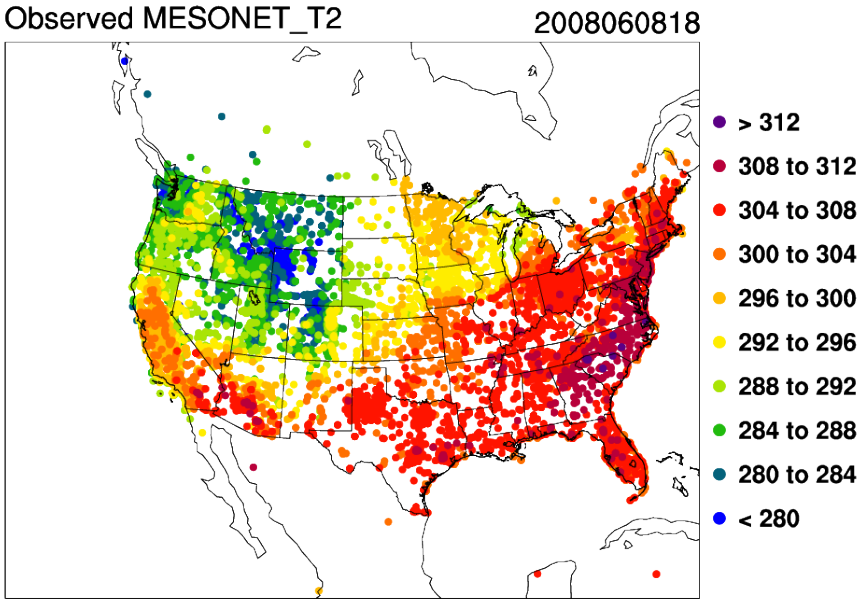
- 50-member ensemble
- WRF/DART to generate analyses and forecast

Cycling period: 1-10 June 2008 (3-hrly)

Observations for data assimilation

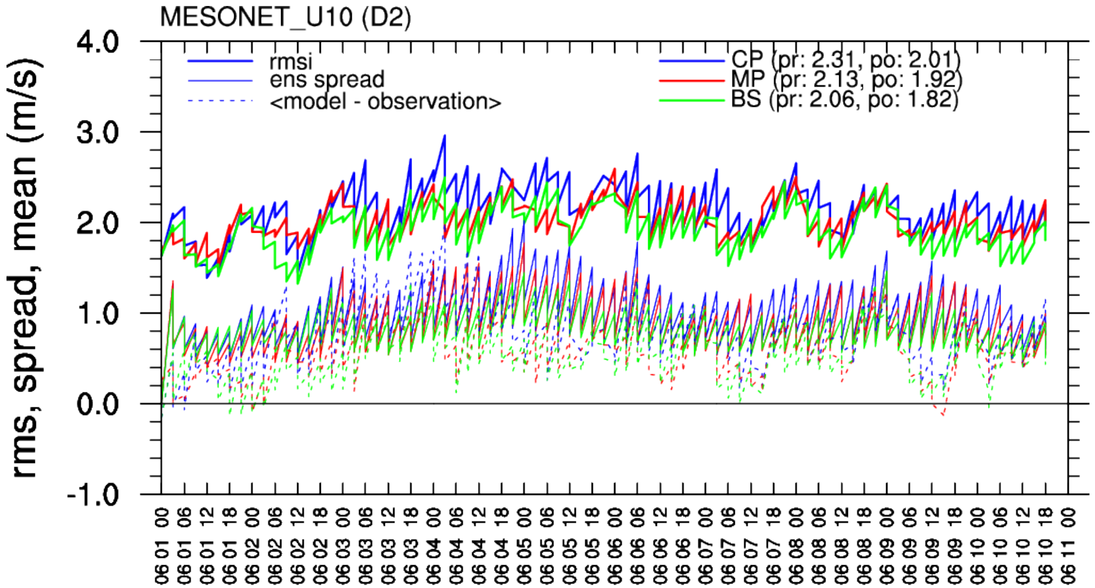
- MADIS (Meteorological Assimilation Data Ingest System)
    - RAOB - u, v, t, td, surface altimeter
    - METAR - u, v, t, td, surface altimeter
    - Marine - u, v, t, td, surface altimeter
    - ACARS - u, v, t, td
  - Surface observations: metar (for assimilation) and integrated mesonet (for verification)



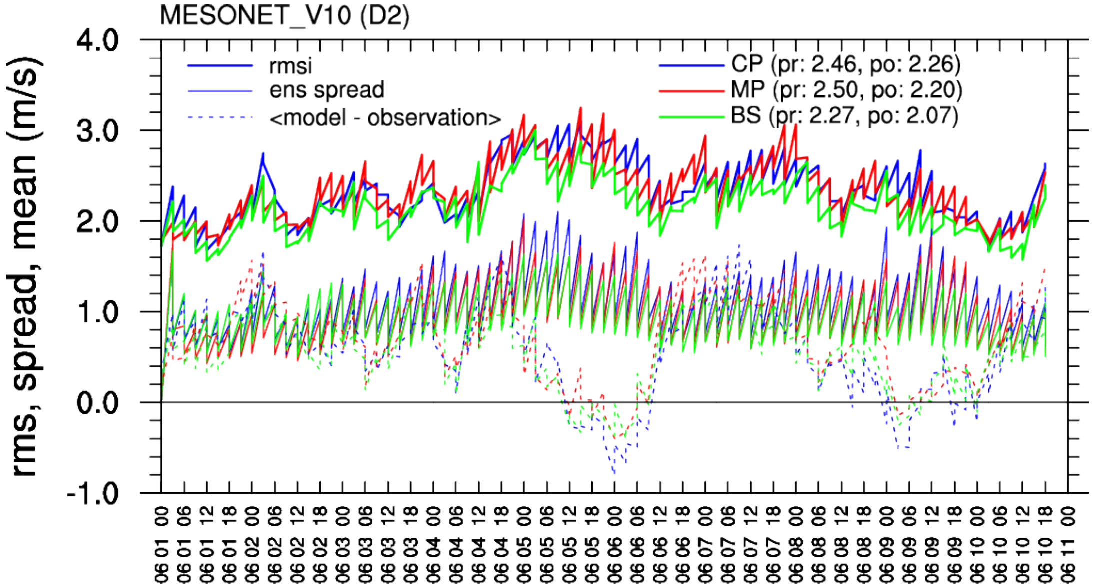


Obs-space diagnostics (mesonet verification)

U10

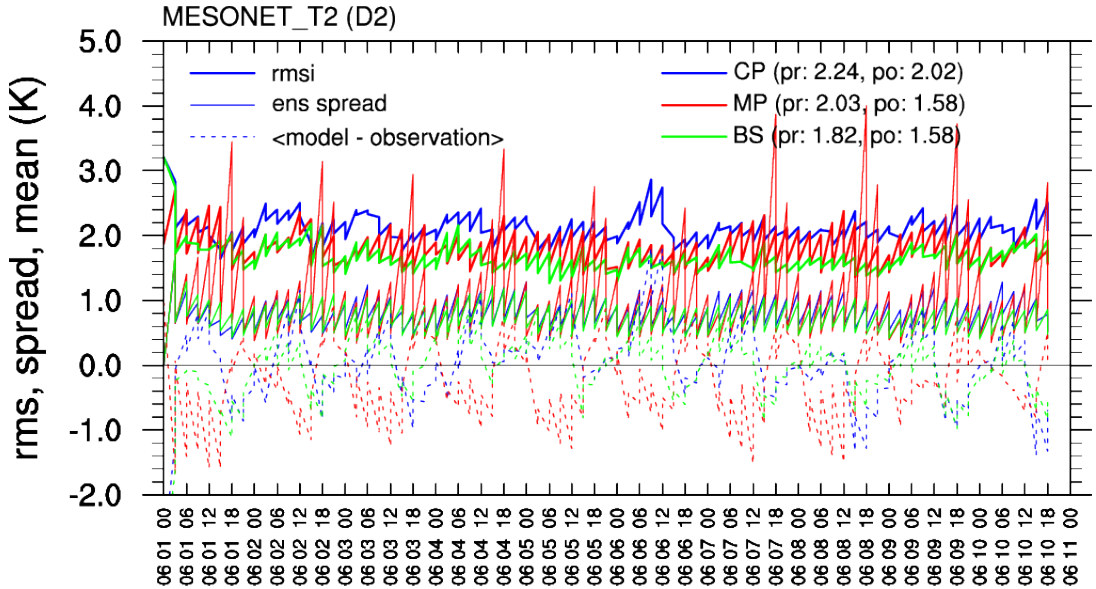


V10

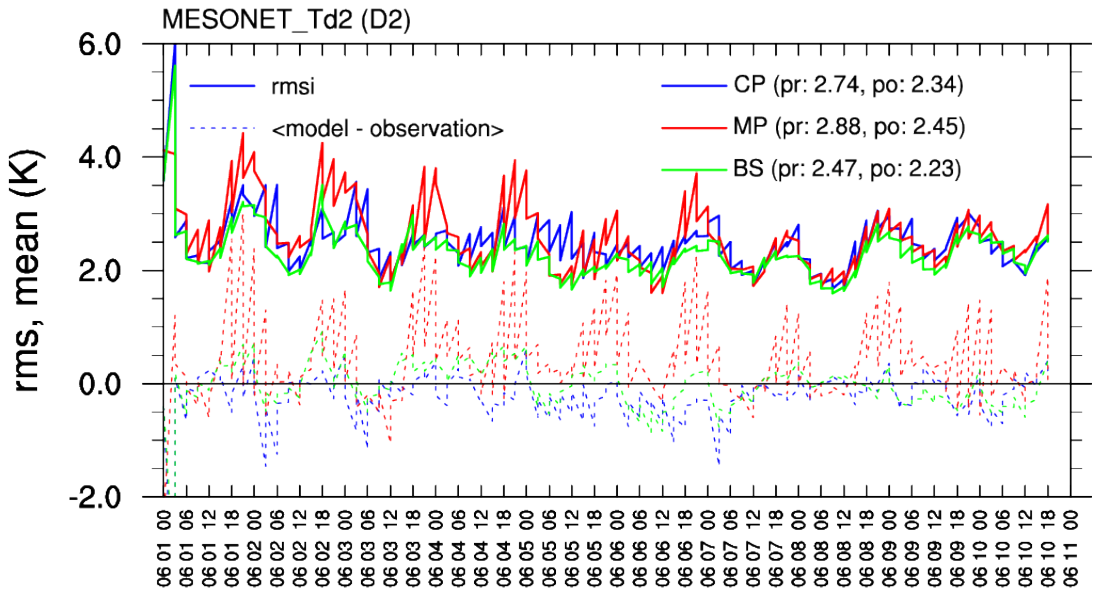


Obs-space diagnostics (mesonet verification)

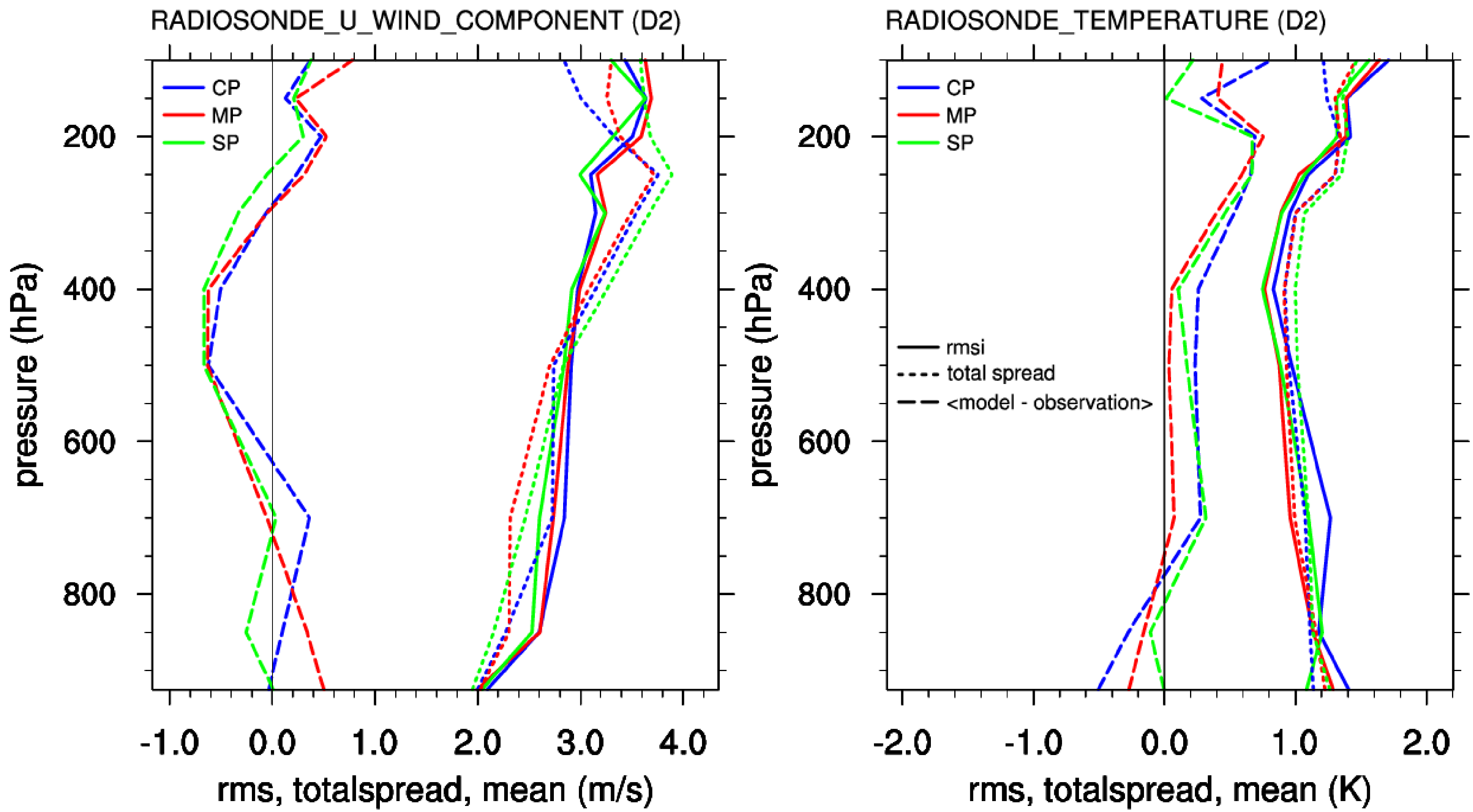
T2



Td2

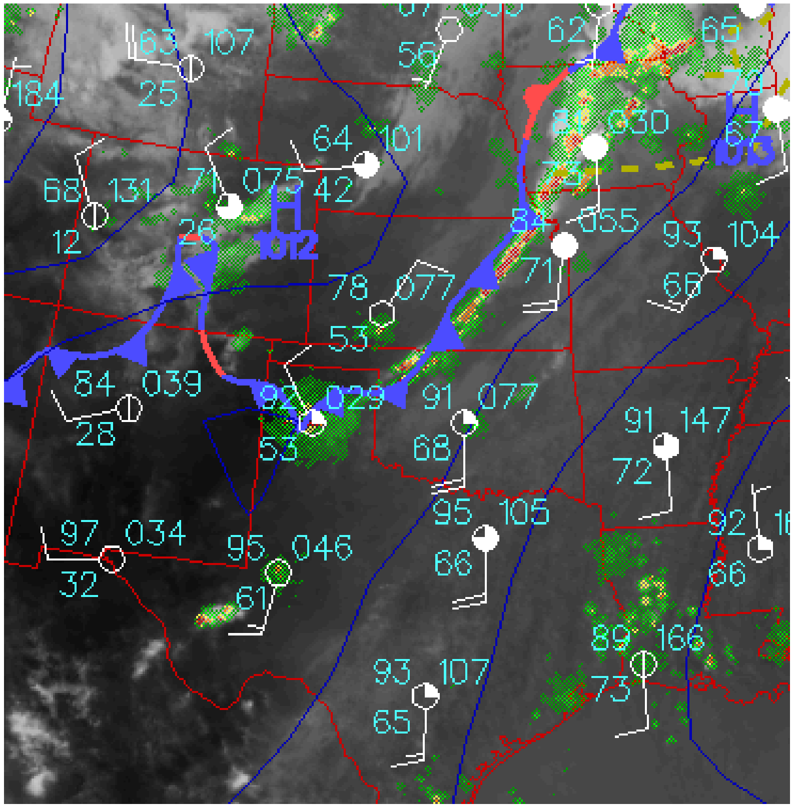


Obs-space diagnostics (sounding)

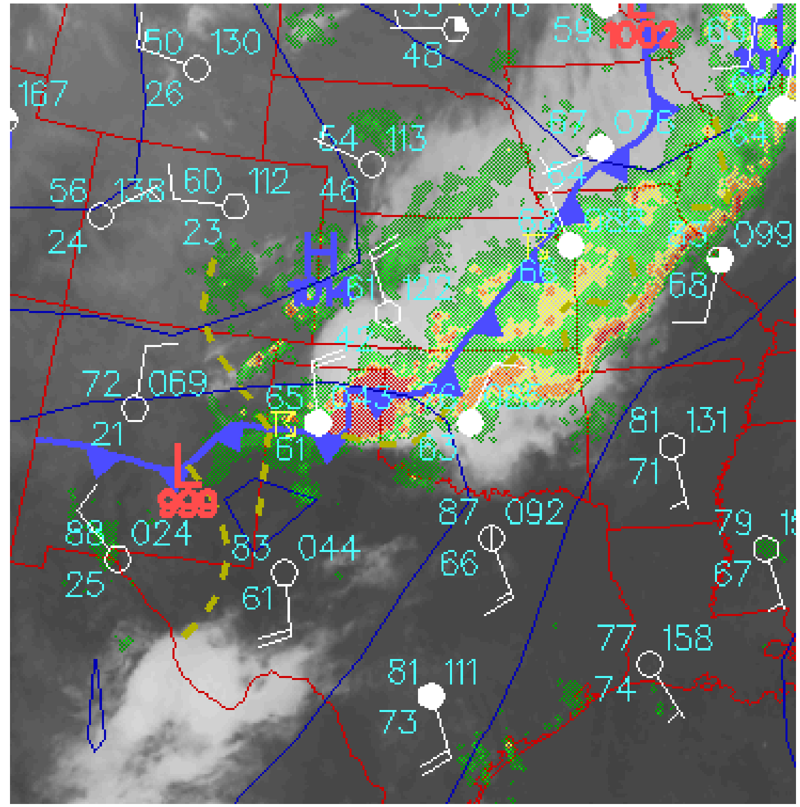


An MCS case in summer’08

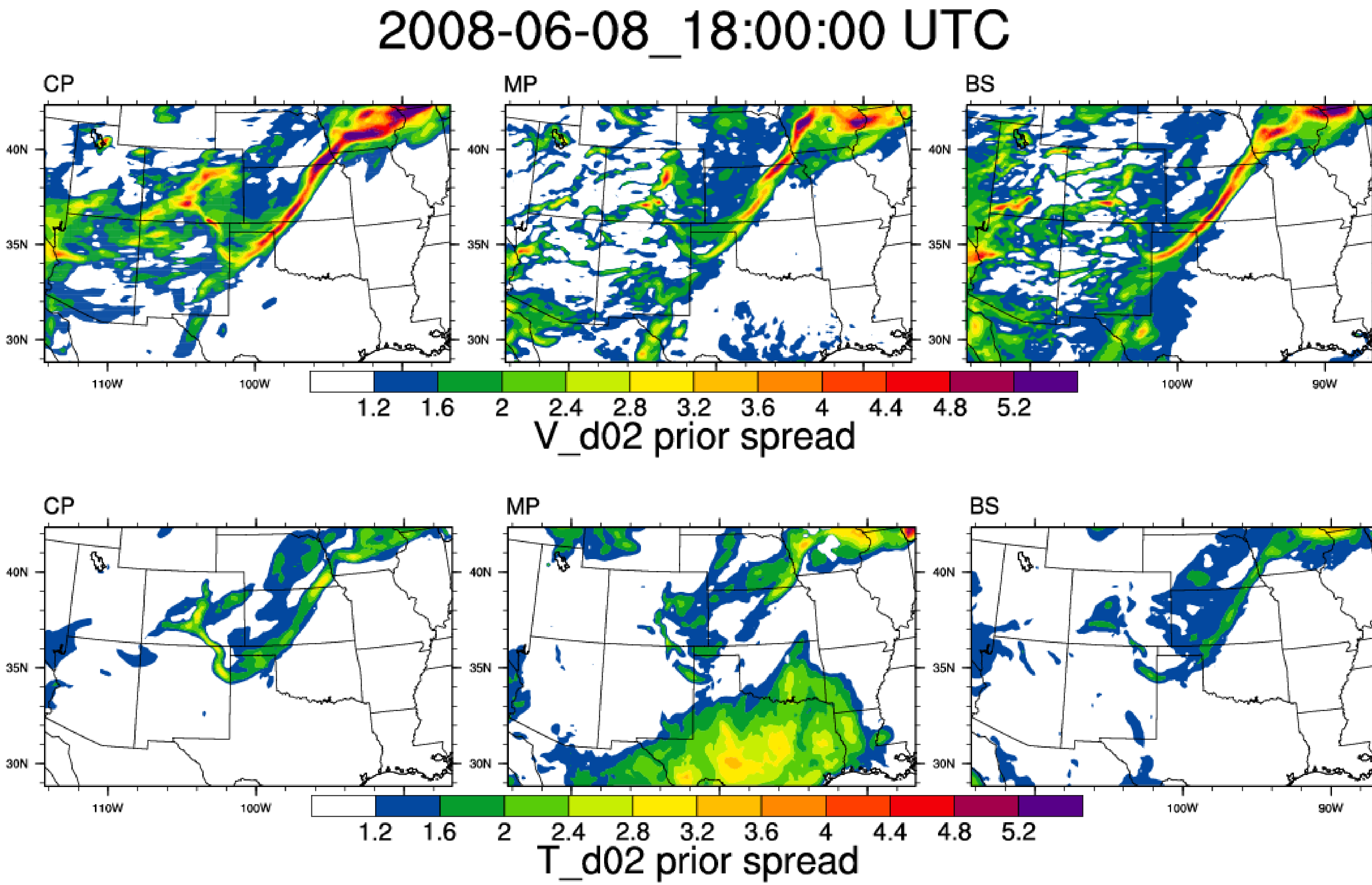
2008-06-08_21:00 UTC



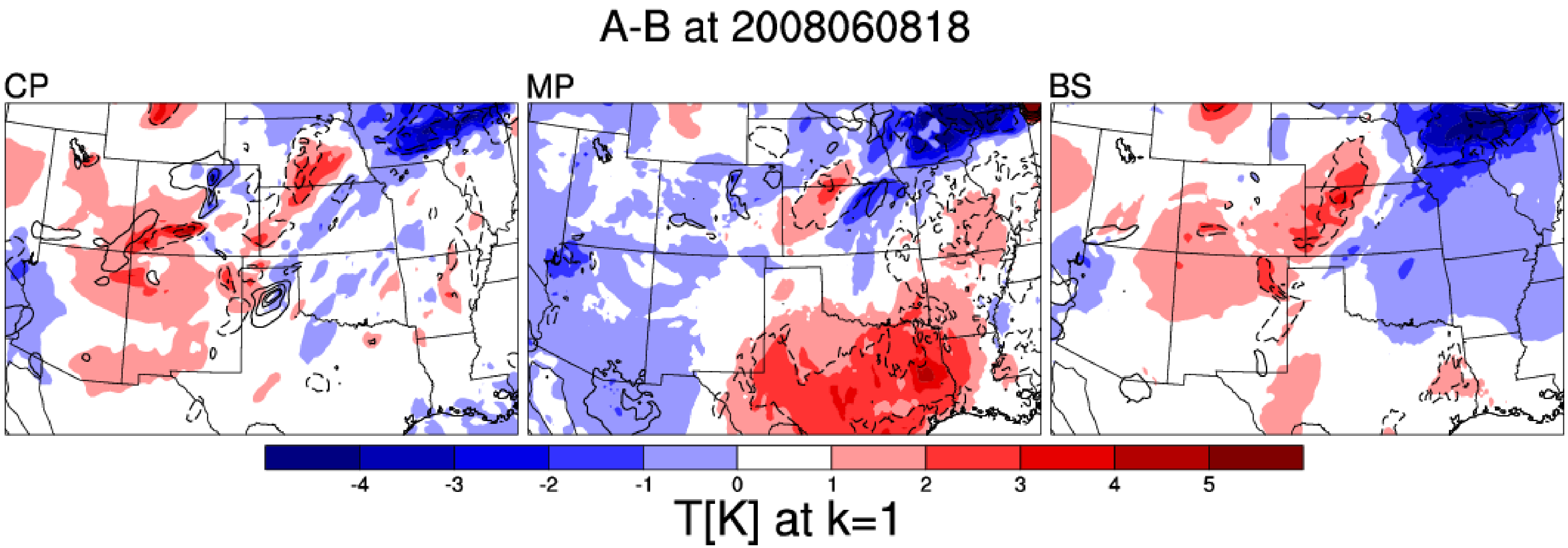
2008-06-09_06:00 UTC



Ensemble spread (3-h forecast)

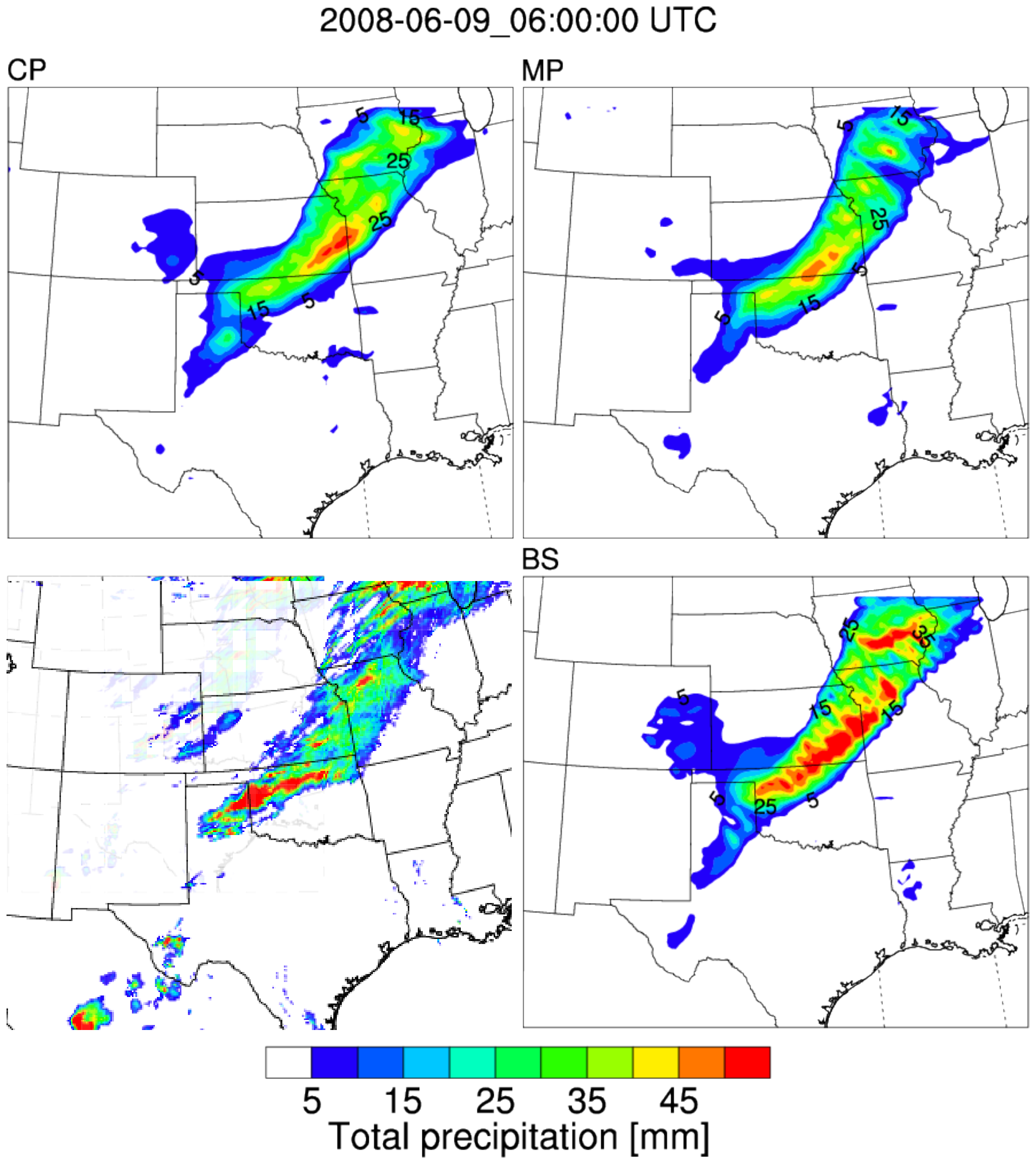


Analysis increment in ensemble mean



12-H accumulated rainfall at 15-km grid

NCEP Stage IV →



Summary for model errors in WRF/DART

- The meso-scale ensemble system generally suffers from under-dispersiveness.
- Including model error representation improves the analysis and the following forecast compared to the control-physics ensemble that uses the same physics combination for all members.
- The stochastic Kinetic Energy Backscatter scheme was well tuned to improve the atmospheric state near the surface. The SKEBS outperforms the multi-physics ensemble in the short-term forecast.
- Multi-physics ensemble needs to be more investigated for the mean bias errors and the overdispersiveness near the surface depending on the physics combinations.

Ongoing work at NCAR

- SKEBS released with WRF3.3.
- Development ongoing: plans to introduce flow-dependent dissipation and vertical structure
- Impact of multi-physics and stochastic backscatter scheme in ensemble data assimilation
- Understand differences between multi-physics and stochastic representation physically
- A perturbed physics-tendency scheme (Buizza et al., 1999) is currently being tested (revisiting from earlier work)
- Extend ensemble forecasts with different model error techniques for probabilistic verification