The NCAR/ATEC Operational Mesoscale Ensemble Data Assimilation and Prediction System – “Ensemble-RTFDDA”

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The NCAR RTFDDA modeling team

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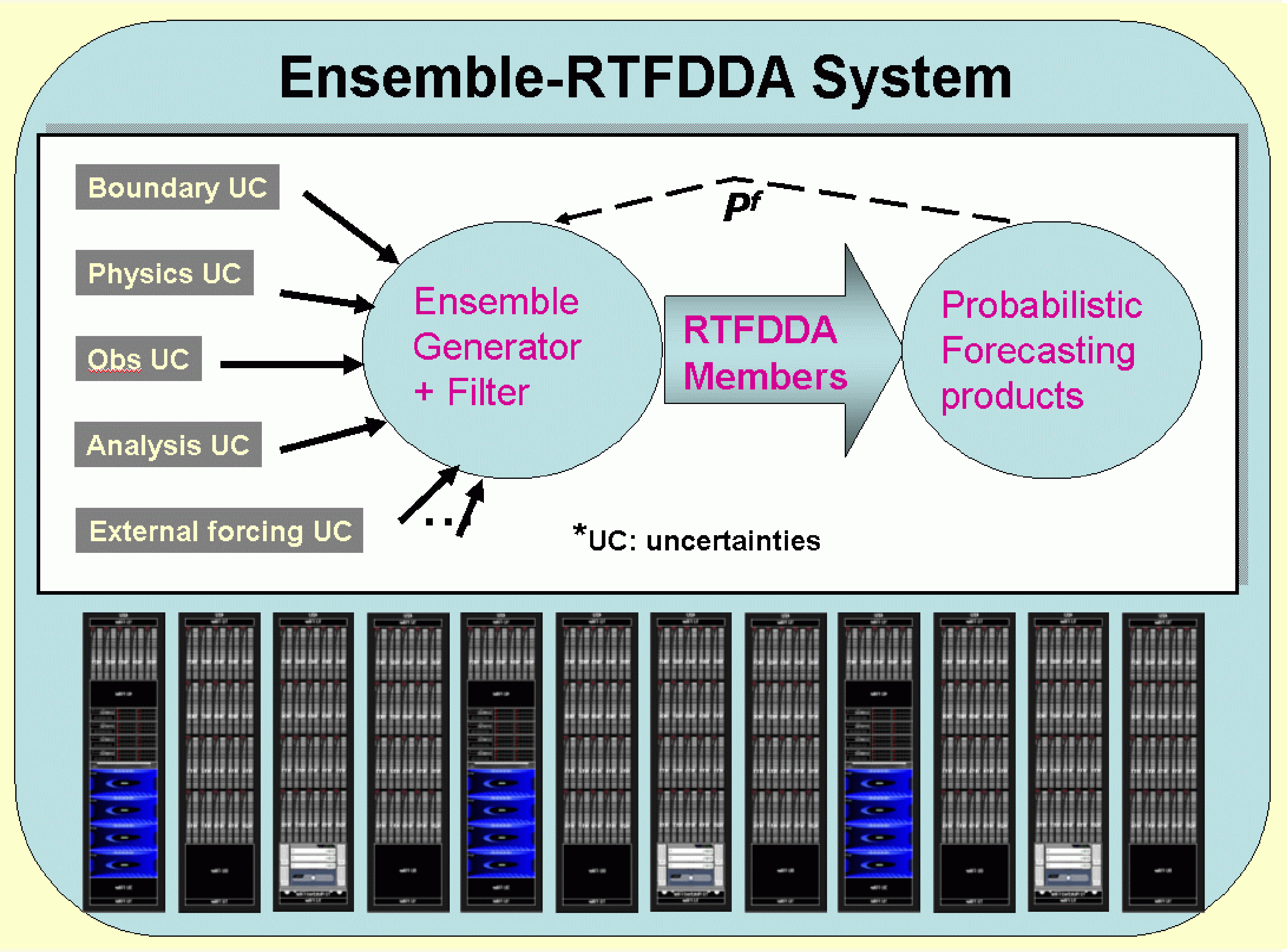
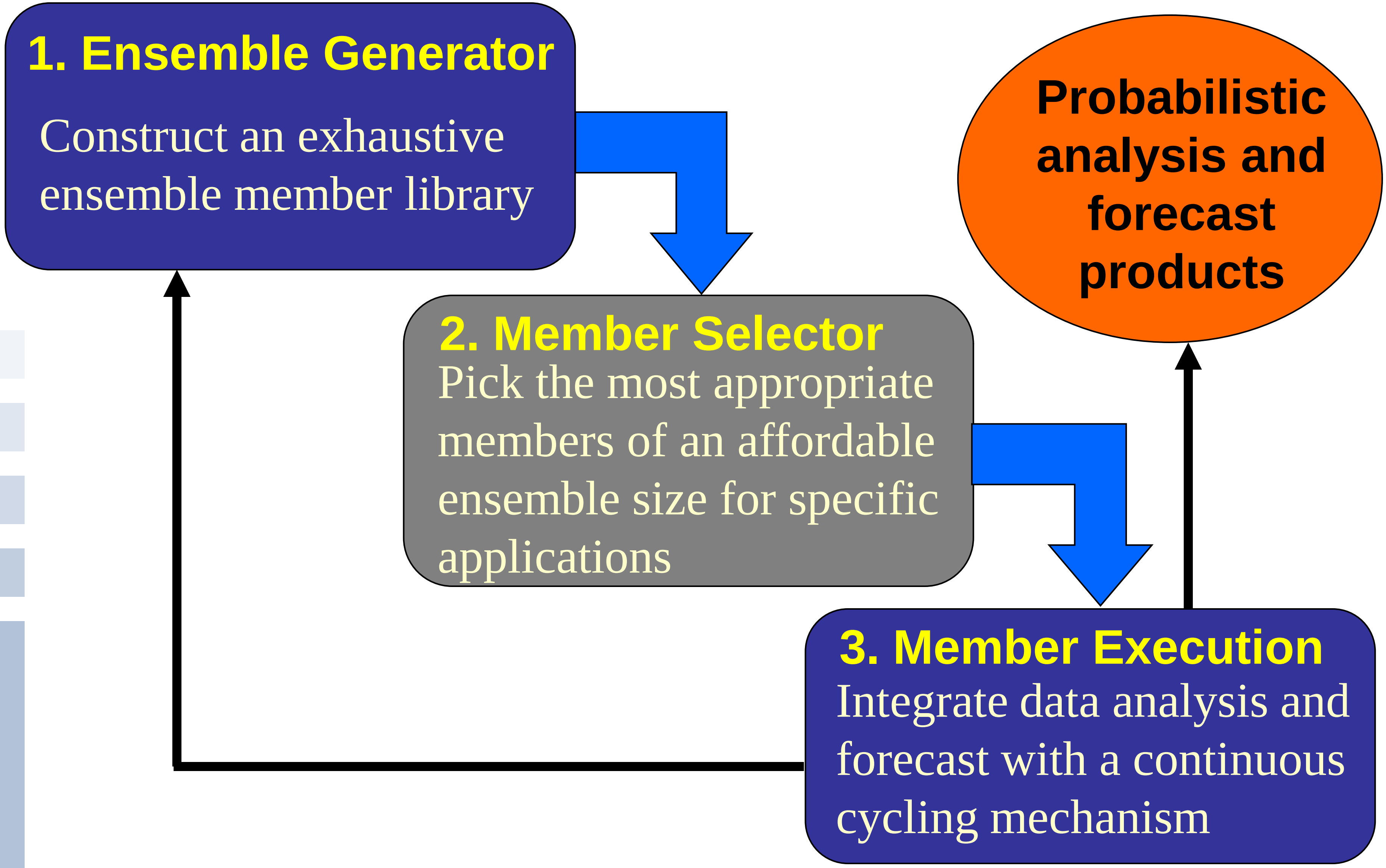
Challenges of Meso-β,γ EPS

- **A multiple (temporal and spatial) scale problems**
  - Uncertainties for small scale different scales differ from those on synoptic scales
  - Uncertainties in boundary conditions
- **Physics plays a critical role**
  - Uncertainties in 100+ parameters of physical schemes
  - Uncertainties in LS and trace gases/aerosol specification
- **Terrain representation**
- **Data assimilation**
  - Uncertainties in observations, B (P^f) and thus analyses
  - Seamless DA and EPS
- **Intuitive probabilistic prediction products**

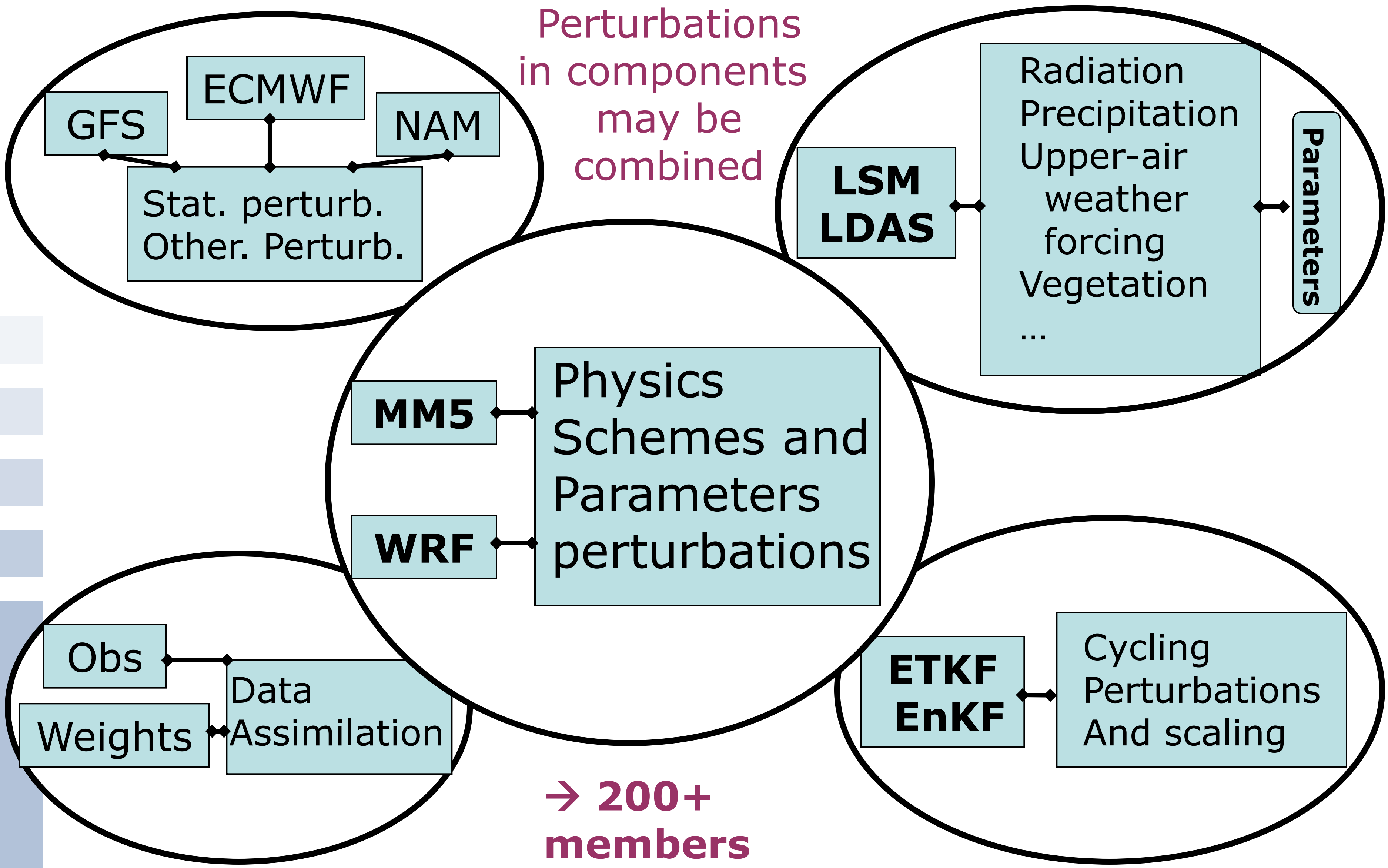
RTFDDA → Ensemble-RTFDDA



E-RTFDDA Implementation: “3-Modules”



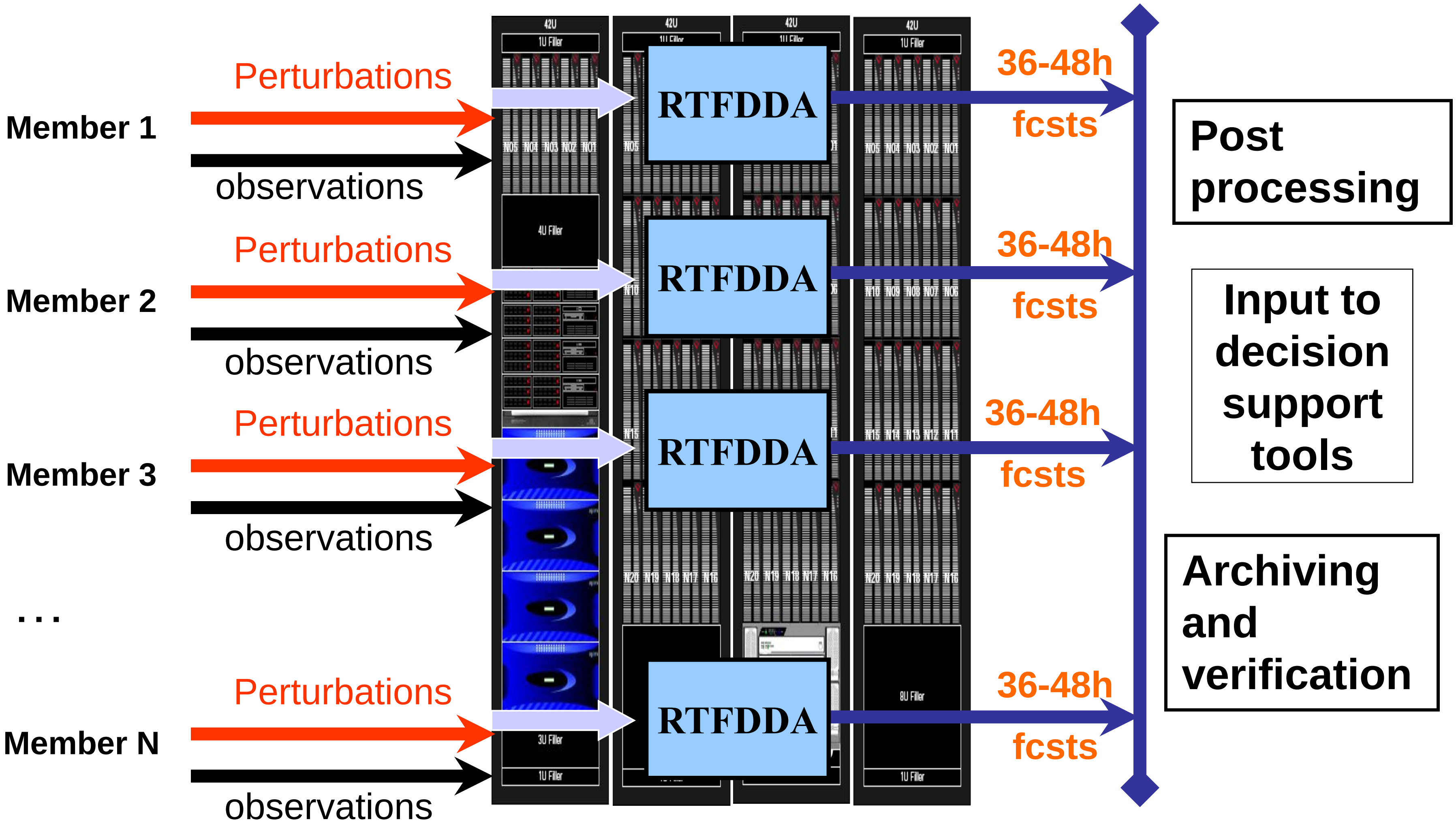
The Ensemble Generator Module



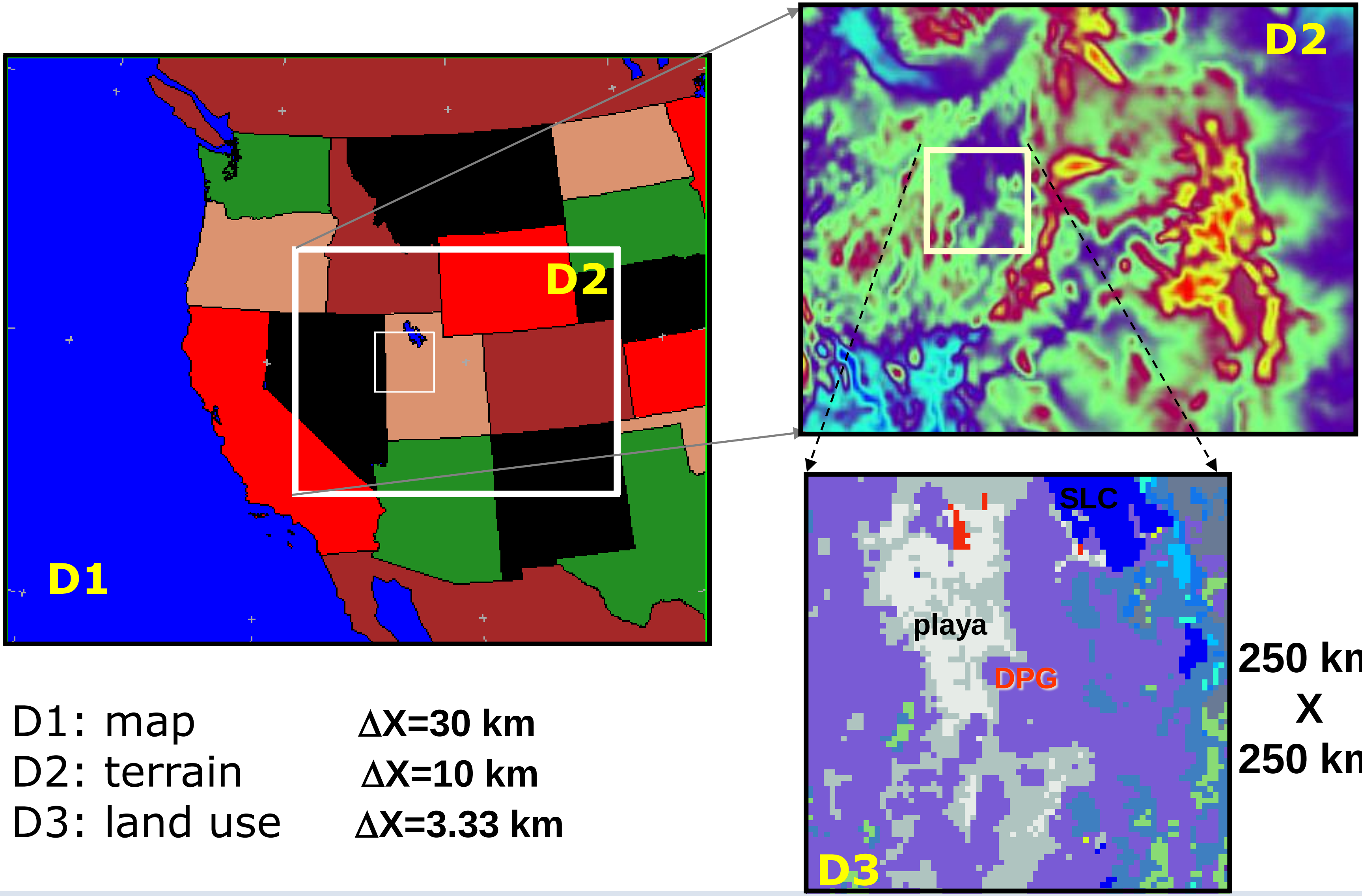
The Member Selection Module

- **Pre-conditions**
  - Typical weather regimes at the application location
  - Weather variables of high interest
- **Objectives**
  - Remove outliers that are persistently verified bad
  - Clear members that provide redundant info
- **Approaches**
  - People in the loop: manual picks
  - Automated: continuously self-training and adjusting
- **Automated perturbation member selection**
  - Optimal sampling for representation of forecast PDF
  - Difficult to implement
  - Affect ensemble calibration implementation

The Ensemble Execution Module



An E-RTFDDA Operation at the Army Dugway Proving Ground Since Aug. 2007



250 km X 250 km

D1: map ΔX=30 km
D2: terrain ΔX=10 km
D3: land use ΔX=3.33 km

30 members, 6h cycles, 42h forecasts

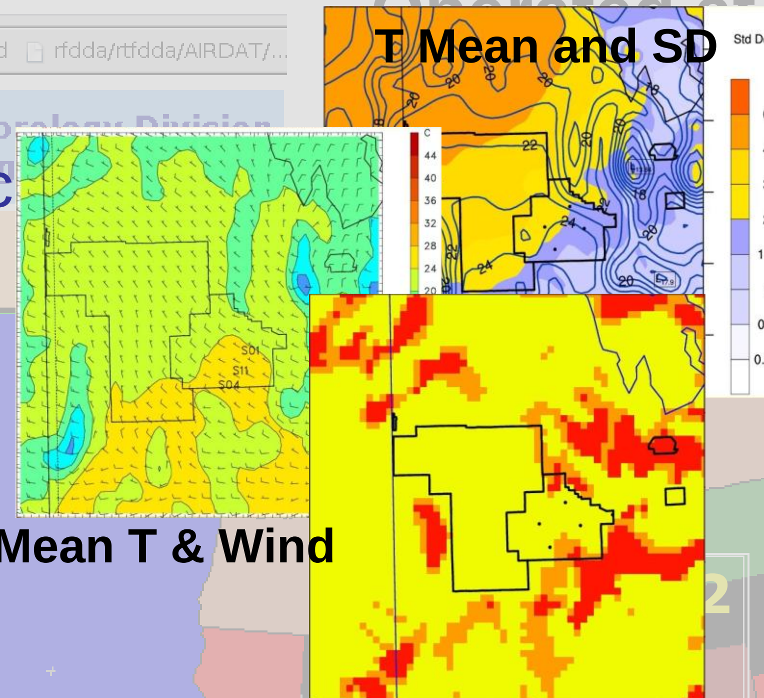
E#	LBC	WRF Members (15)
1	NAM	Control: WRF baseline physics
2	GFS	Control: WRF baseline physics
3	NAM	SLAB land surface
4	NAM	MYJ PBL
5	NAM	MYJ PBL + GD Cumulus
6	NAM	WMS6 microphysics
7	NAM	GD cumulus
8	GFS	Thomason microphysics
9	GFS	MYJ PBL + WMS5 microphysics
10	GFS	MYJ PBL
11	GFS	MYJ PBL + GD Cumulus
12	GFS	BMJ cumulus
13	GFS	BMJ cumulus in 3.3 km grid
14	GFS	GD cumulus in 3.3 km grid
15	GFS	KF cumulus in 3.3 km grid

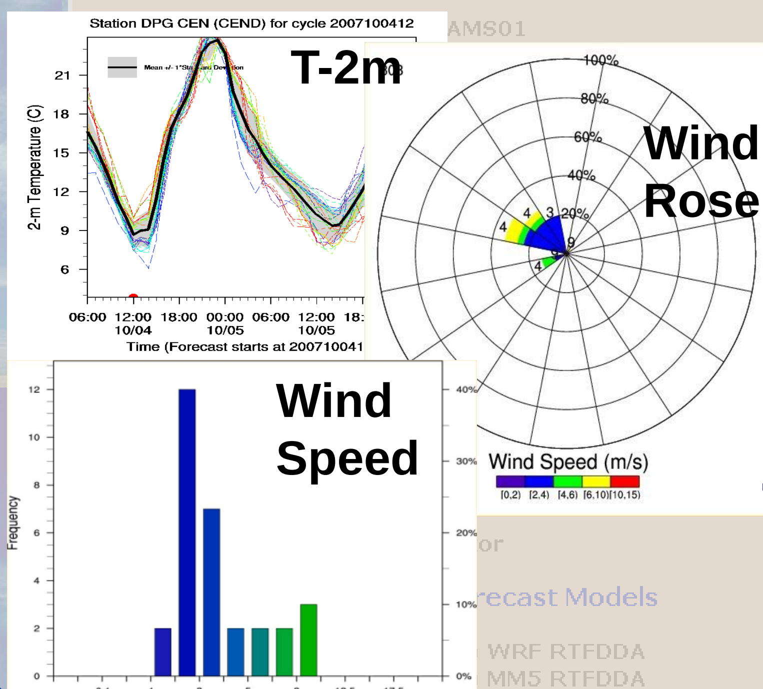
E#	LBC	MM5 Members (15)
16	NAM	Control: MM5 baseline physics
17	GFS	Control: MM5 baseline physics
18	NAM	Simple cloud-effect radiation
19	NAM	ETA TKE PBL
20	NAM	Kain-Fritsch cumulus
21	NAM	Goddard microphysics
22	GFS	Betts-Miller cumulus
23	GFS	Reisner 3-ice microphysics
24	GFS	CCM2 radiation
25	GFS	GFS LBC Phase-uncertainty 1
26	GFS	Symmetric perturb to Member 25
27	GFS	GFS LBC Phase-uncertainty 2
28	GFS	Symmetric perturb. to Member 27
29	GFS	Correlated sounding perturbation
30	GFS	Symmetric perturb. to Member 29

Real-time Operational Products for DPG

Surface and X-sections

– Mean, Spread, Exceedance Probability, Spaghetti, …

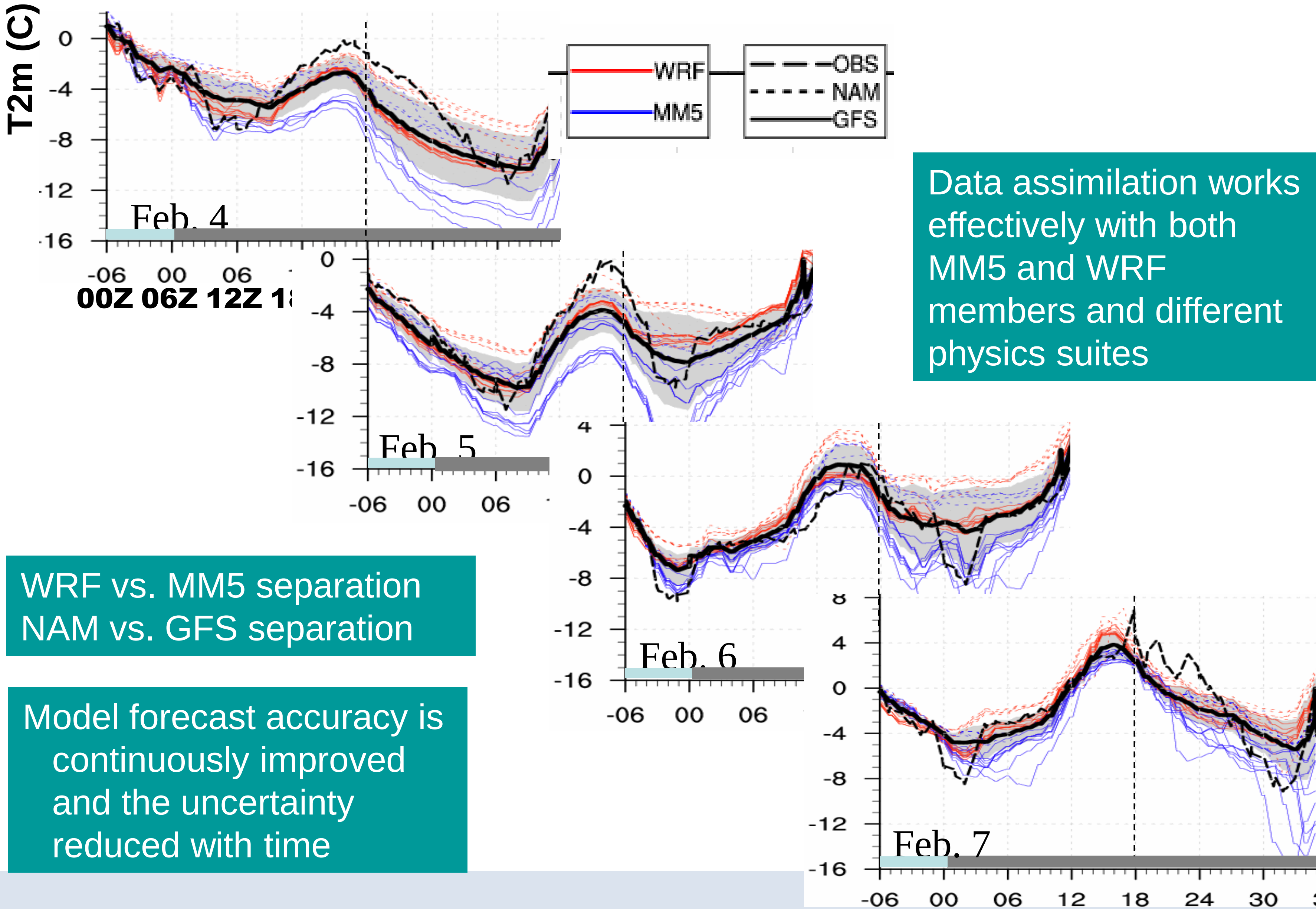




Pin-point Surface and Profiles

– Mean, Spread, Exceedance probability, spaghetti, Wind roses, Histograms …

2-m Temperatures for the 06Z Cycles on 4 – 7 Feb. 2008 at DPG SAMS8

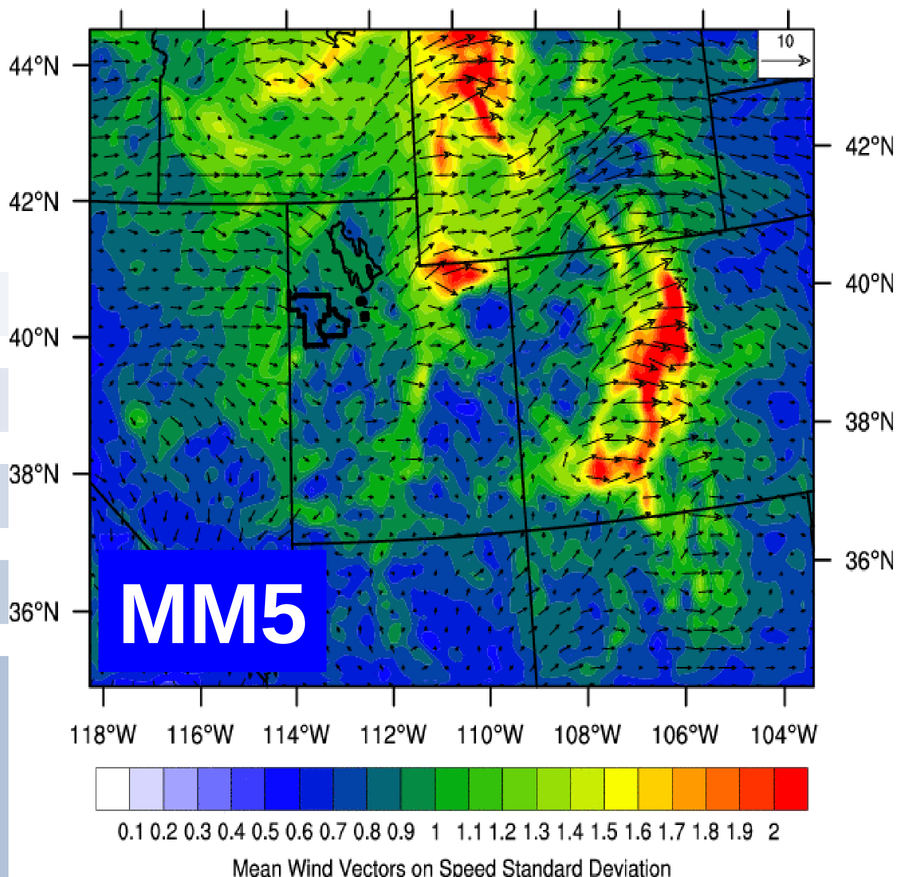


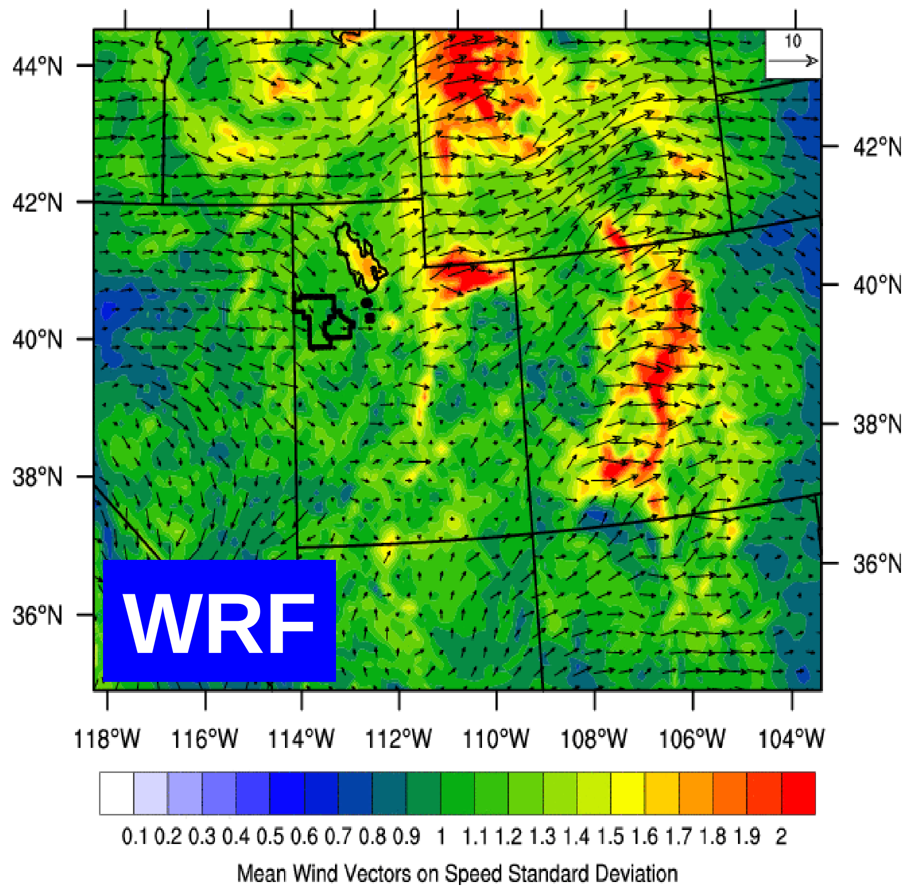
Data assimilation works effectively with both MM5 and WRF members and different physics suites

WRF vs. MM5 separation
NAM vs. GFS separation

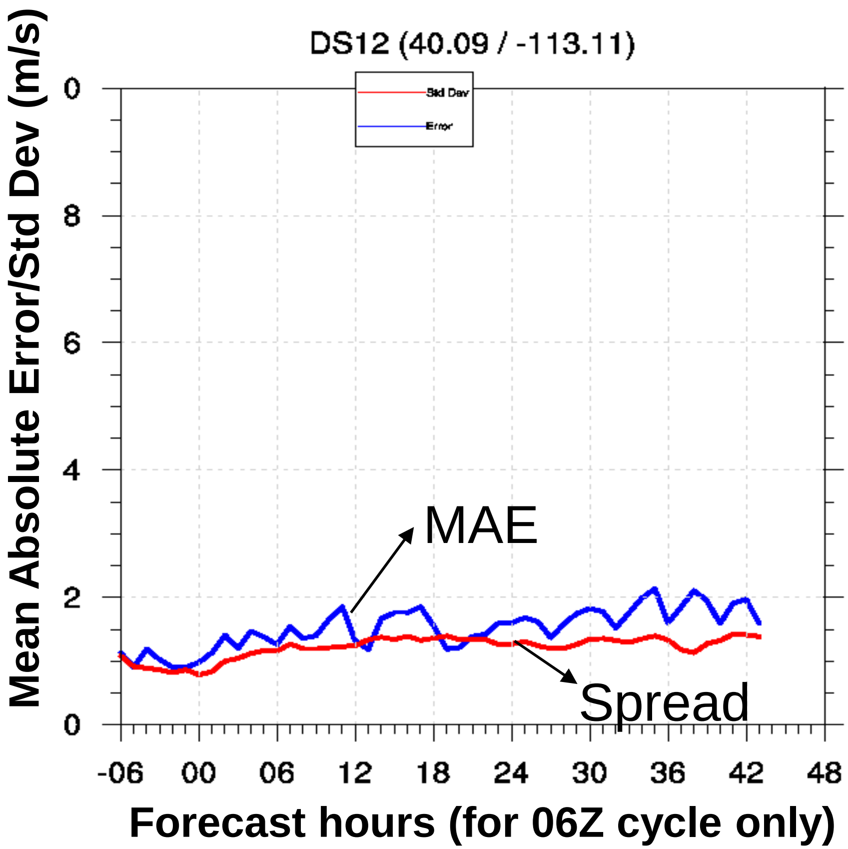
Model forecast accuracy is continuously improved and the uncertainty reduced with time

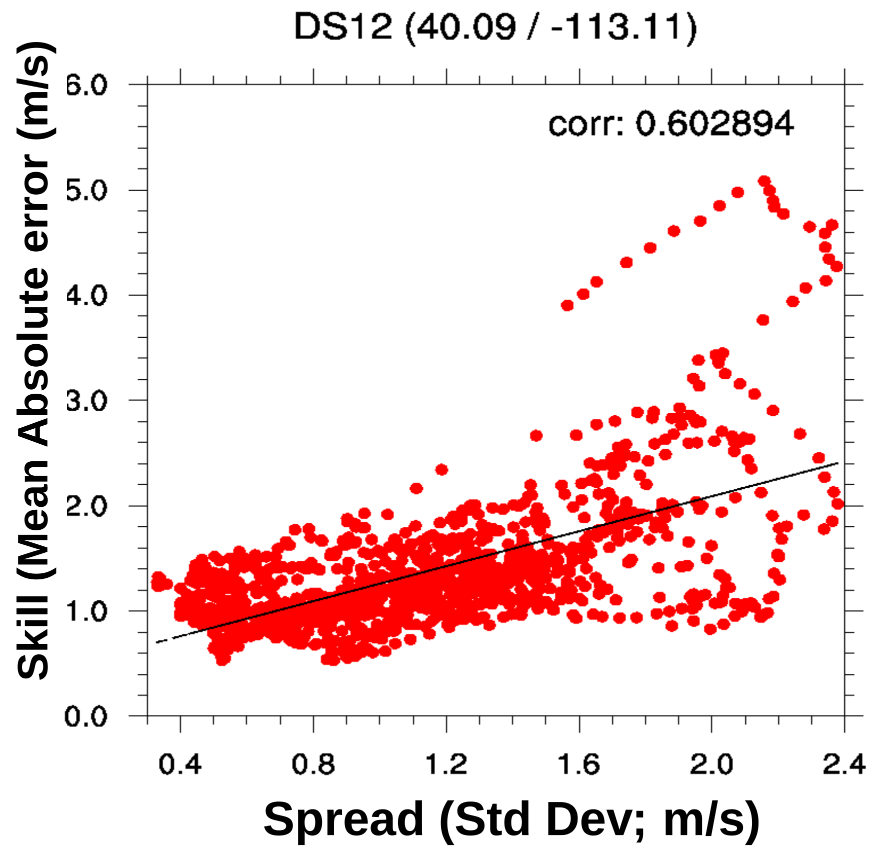
10-m Winds Mean Vectors and Speed Spread
36h Forecasts Valid at 18Z (Feb. – Mar. 2008)



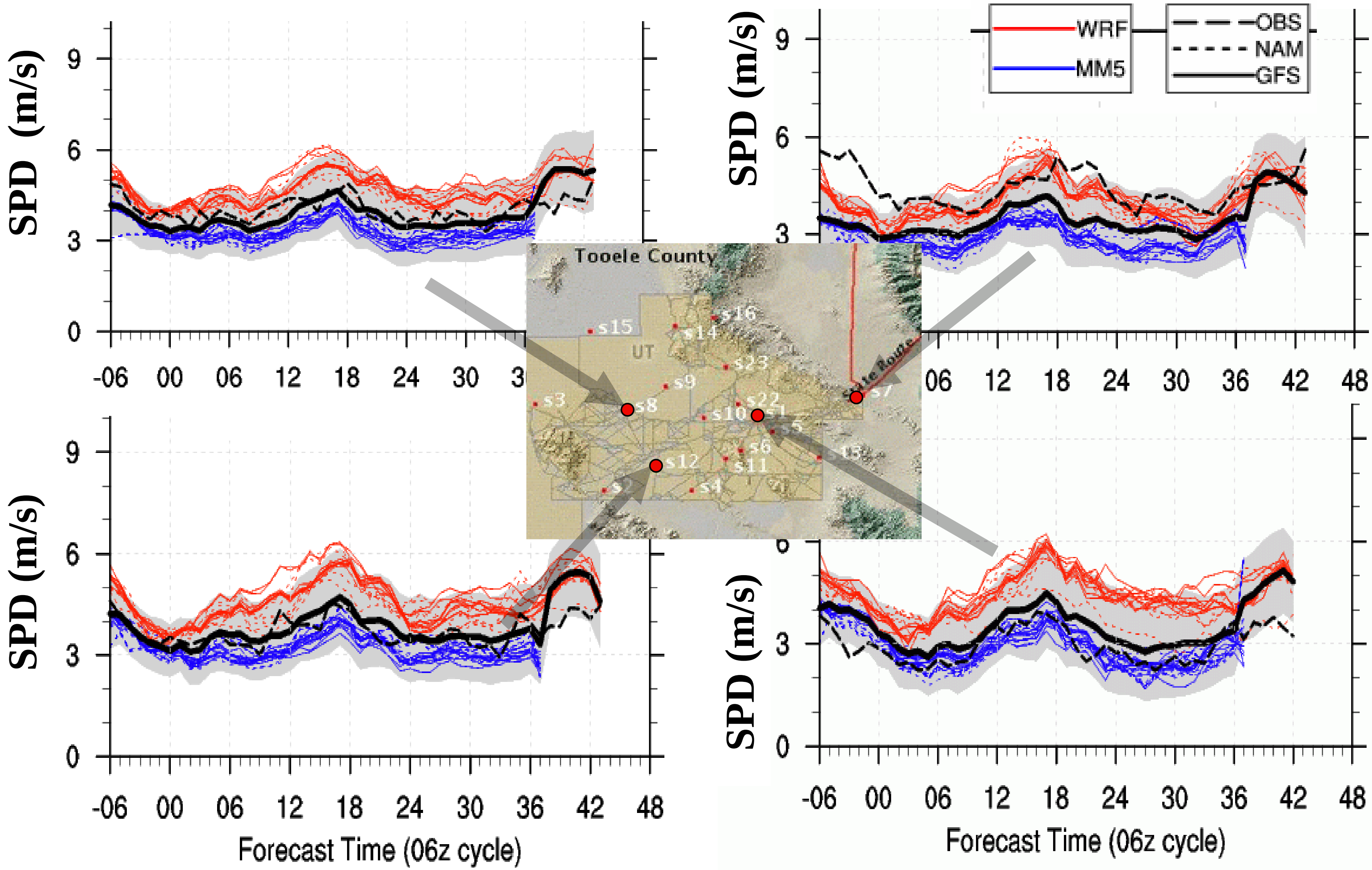


10-m Wind Speed Spread-skill Correlation at SAMS12

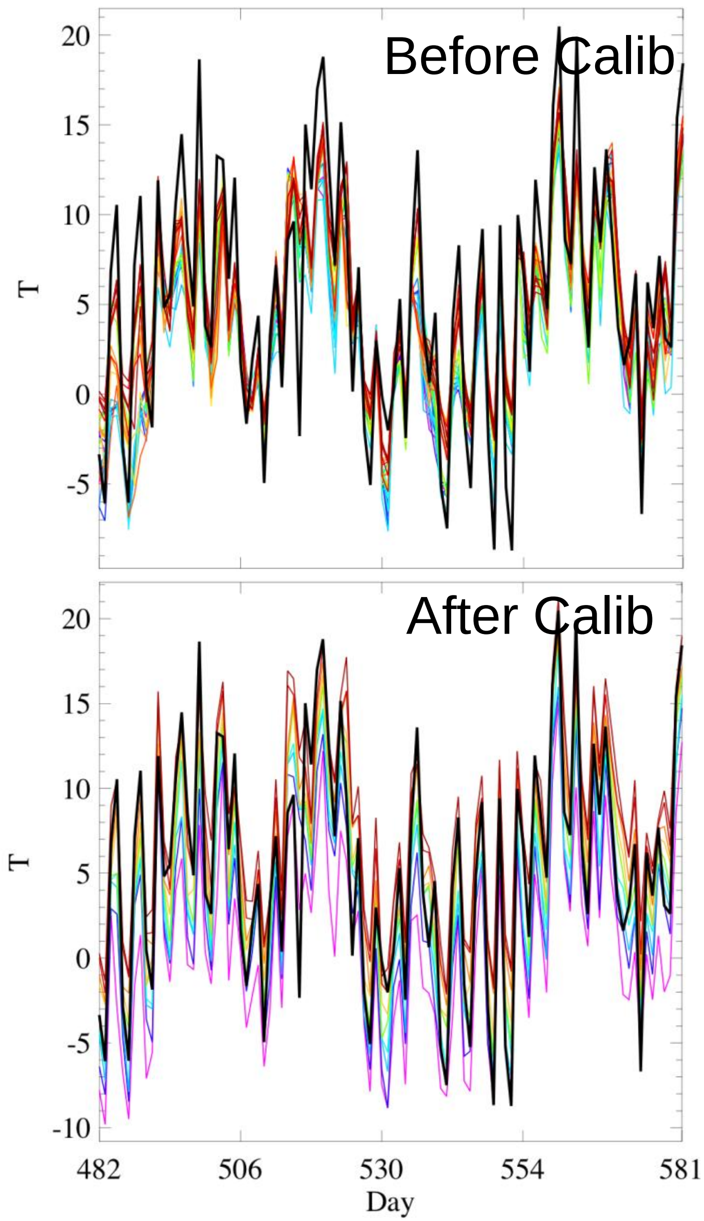




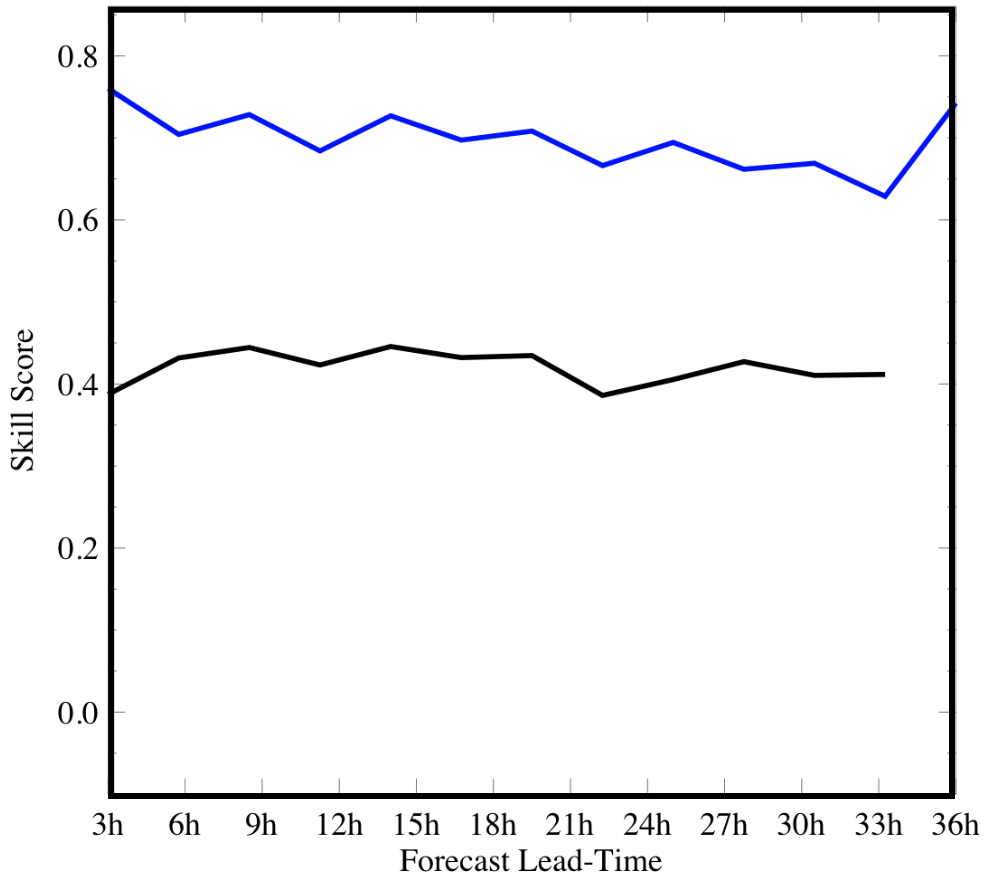
2008 Feb-Mar Mean: 10-m Winds



36hr Temperature Calibration with Quantile Regression (DPG SAM 12)



RMSE Skill Score



A 4D Relaxation Ensemble Kalman Filter

Obs-nudging:

$Dx/Dt = \ldots + G\,W\,(y^o - Hx^f)$

$W = W_q\, W_{time}\, W_{horizontal}\, W_{vertical}$

EnKF:

$$x^a = x^f + Ke(y^o - Hx^f)$$

$$Ke = P_e^f H^T (HP_e^f H^T + R)^{-1}$$

$$P^a = (I - KH)P_e^f$$

Obs-nudging → EnKF:

$X^a = X^f + \Delta tGW\,(y^o - Hx^f)$ ← one Δt nudging

where $X^f = X_{t-1} + \Delta t\,(\ldots)$

EnKF: $\Delta tGW = K_e$ ← EnKF

4D-REKF: $\Delta tGW = G\,W_q W_{time} K_e$ ← Nudging-EnKF

$$Dx/Dt = \ldots + GW_q W_{time} K_e\,(y^o - Hx_{model})$$

Essence of 4D-REKF(S)

- **Combines obs-nudging E-RTFDDA and EnKF**
  - E-RTFDDA → Error covariance → Kalman Gain
  - Kalman Gain → Obs-nudging weight → (E-)RTFDDA
  - Kalman Filter → I.C. perturbations → E-RTFDDA
- **For this relaxation filter, the structures of error covariance are critical, but not their magnitudes.**
- **4D-REKF(S) produces "spun-up" current analyses and I.C.s for forecasting.**
- **Indirect observations can be assimilated.**
- **Development is in process: DART → E-RTFDDA**

Summary and Conclusions

- E-RTFDDA: relocatbale, multi-model, multi-approach and multi-scale, continuously cycling mesoscale ensemble analysis and forecasting.
- Supporting meso-β,γ scale applications
- Verification indicates benefit of multi-model approaches, importance of model physics and terrain-induced predictability.
- QR calibration improves the probabilistic forecasts and helps identify redundant and outlier members.
- E-RTFDDA new development: A seamless, hybrid obs-nudging and (DART) EnKF mesoscale ensemble data assimilation and prediction algorithm (4D-REKF).