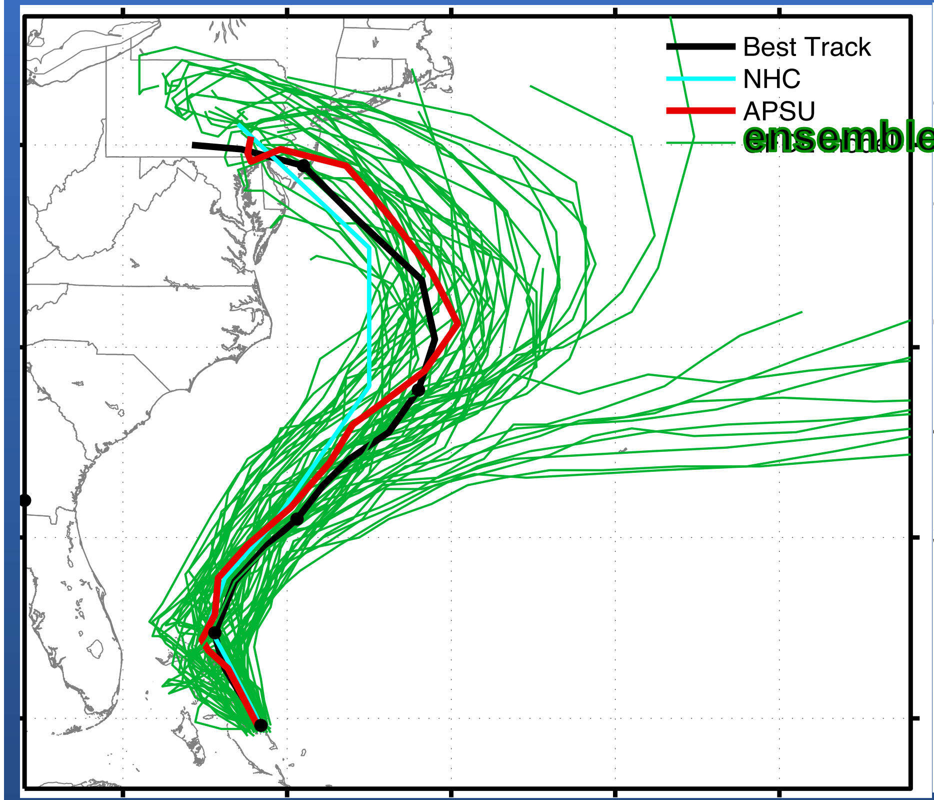
Science Perspectives of Challenges and Opportunities for Regional-scale Data Assimilation and Ensemble Prediction

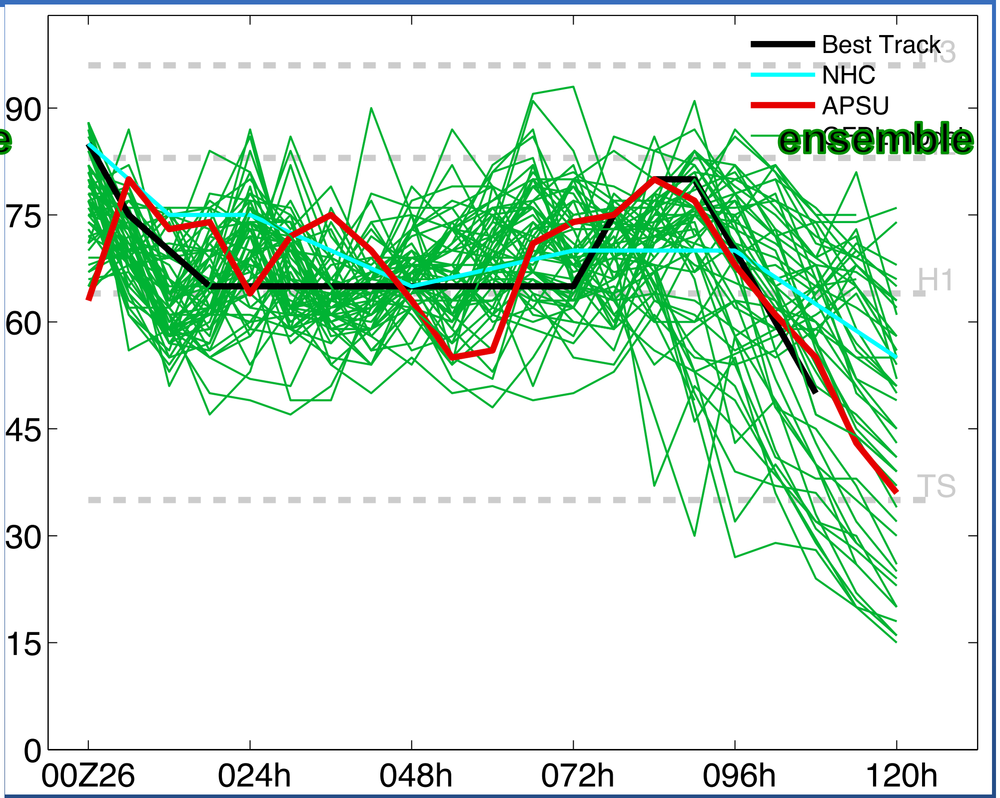
Fuqing Zhang
Penn State University

Cloud-resolving Regional Ensemble Analysis/Prediction

PSU WRF-EnKF Realtime Performance for Sandy

60-member 3-km cloud-resolving ensemble analysis forecast from 00Z Oct 26





Our HFIP experience sponsored by NSF, ONR and NOAA

Lessons Learned from HFIP Experience

- **Hurricane forecast can be greatly improved through cloud resolving ensemble analysis and prediction with assimilation of high-resolution inner-core observations**

- **Future of hurricane prediction: enhanced inner-core observations, advanced data assimilation, improved forecast models, better computing resources for cloud-resolving ensemble**

Practical Predictability vs. Intrinsic Predictability

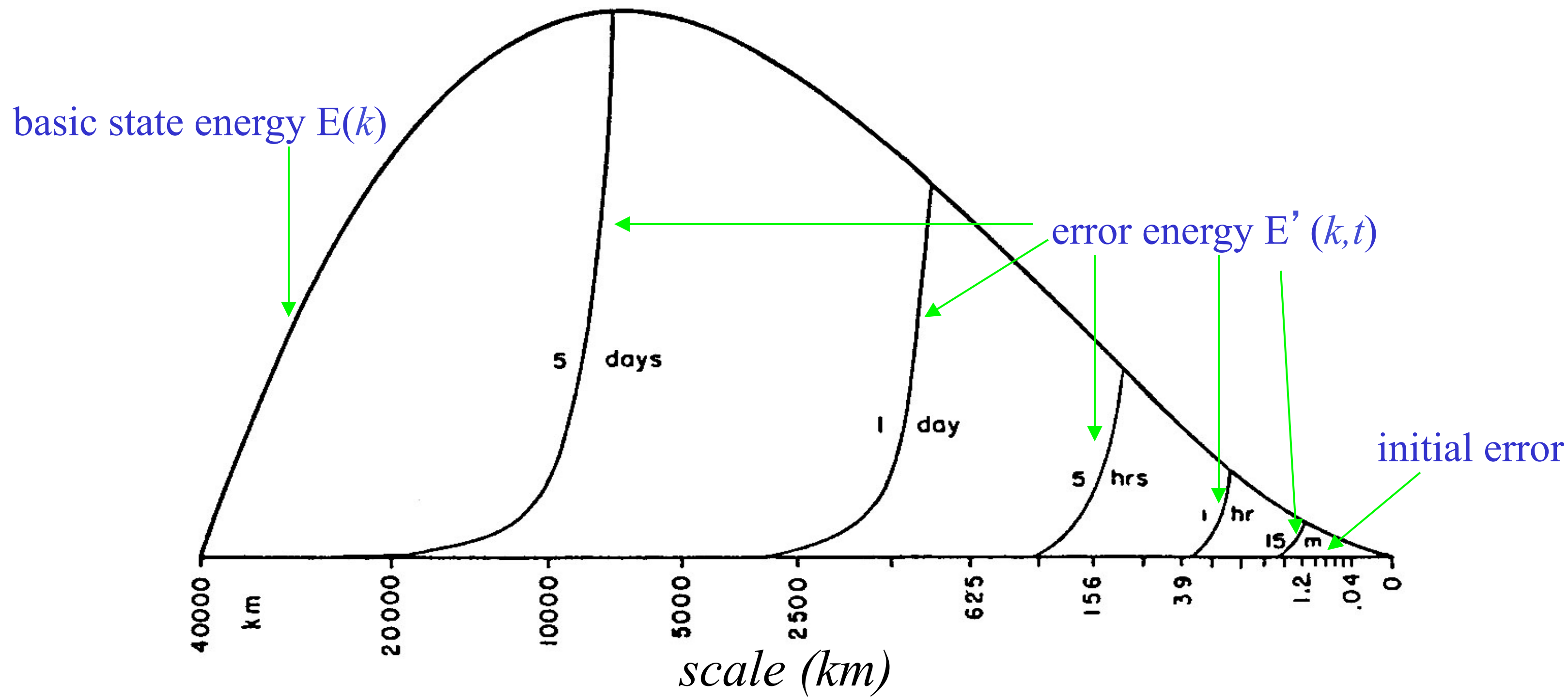
(Lorenz 1996; Zhang et al. 2006; Melhauser and Zhang 2012)

Practical predictability: the ability and uncertainty to predict given practical initial condition uncertainties and/or model errors, both of which remain significantly big in the present-day forecast systems.

Intrinsic predictability: the limit to predict given nearly perfect initial conditions and nearly perfect forecast systems, in other words when the initial condition and model errors become infinitesimally small.

Implication: setting up expectations and priorities for advancing deterministic mesoscale forecasting (through better model, observing network and/or data assimilation); guidance on the design of mesoscale ensemble prediction systems (through understanding of the mesoscale error growth mechanisms)

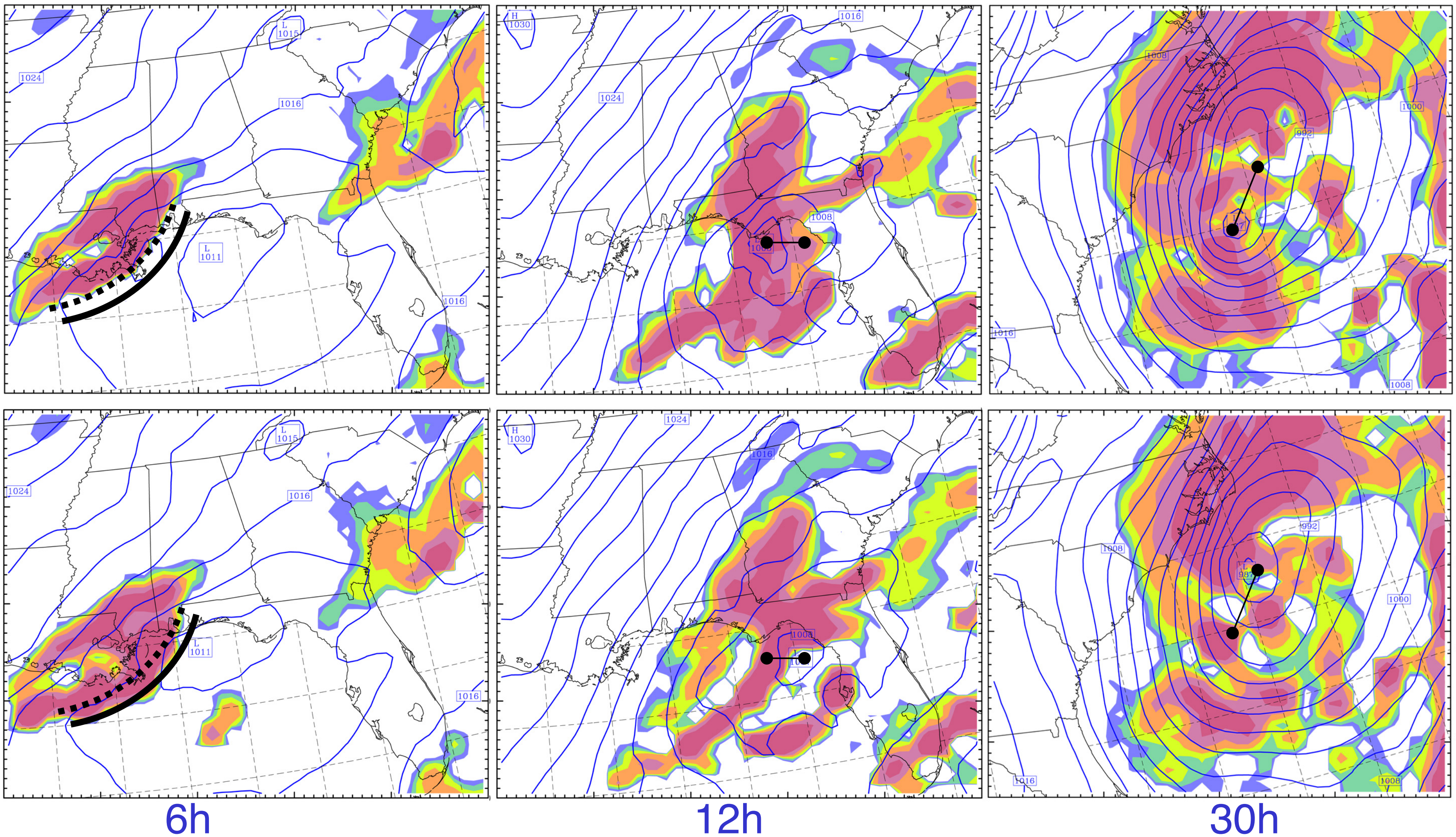
Multi-Scale Predictability Foreseen by Lorenz (1969)



"An error in observing a thunderstorm, after doubling perhaps every fifteen minutes until it becomes large, may subsequently lead to an error in a larger scale of motion, which may then proceed to double every five days. If this is the case, cutting the original error in half would increase the range of predictability of the larger scale not by five days but by only fifteen minutes."

Mesoscale Predictability of a Winter Snowstorm

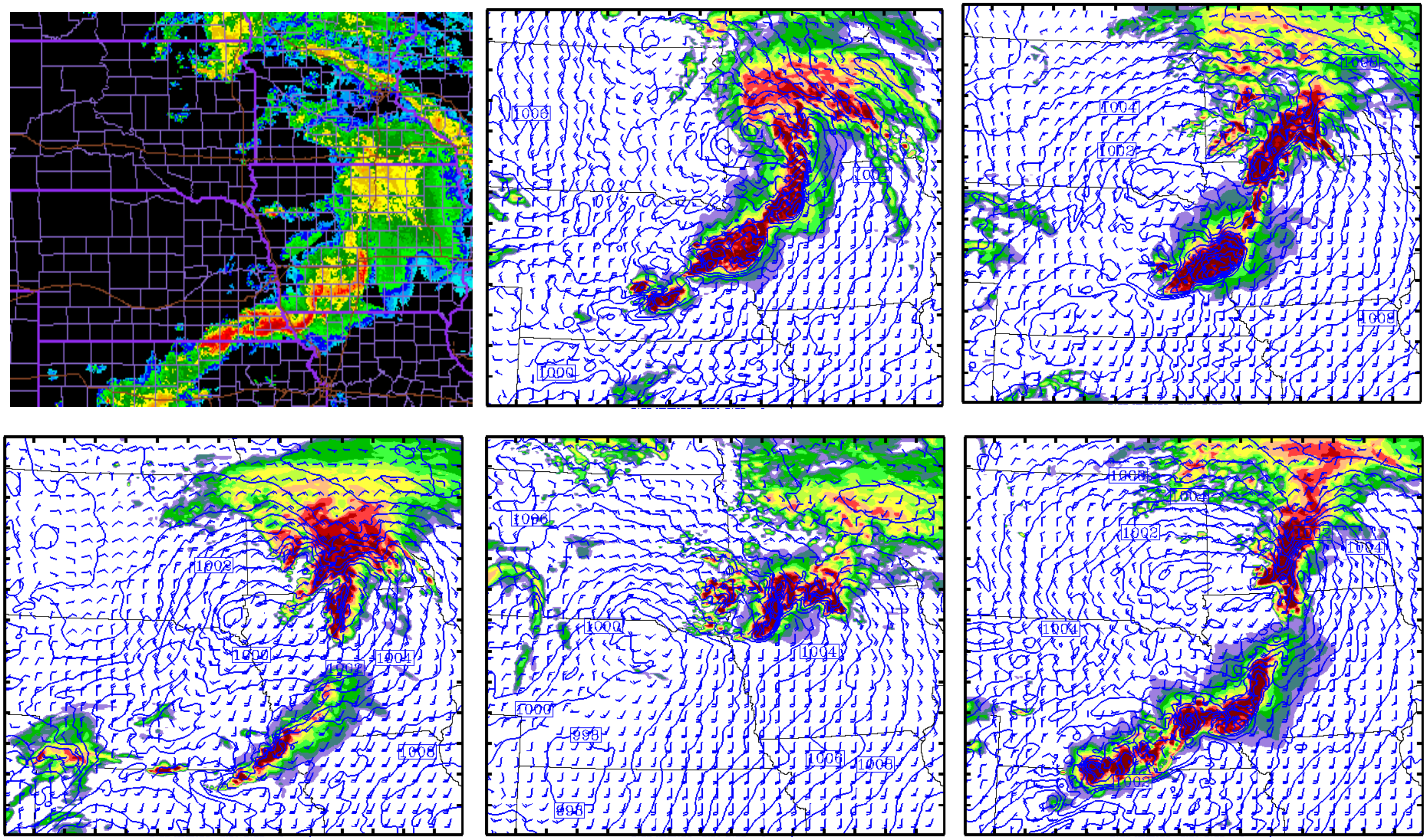
MSLP and reflectivity for w/ and w/o small random white noise in initial temperrature



Zhang, Snyder and Rotunno (2002MWR; 2003 JAS)

Predictability of 10 Jun 2003 Bow Echo event during BAMEX

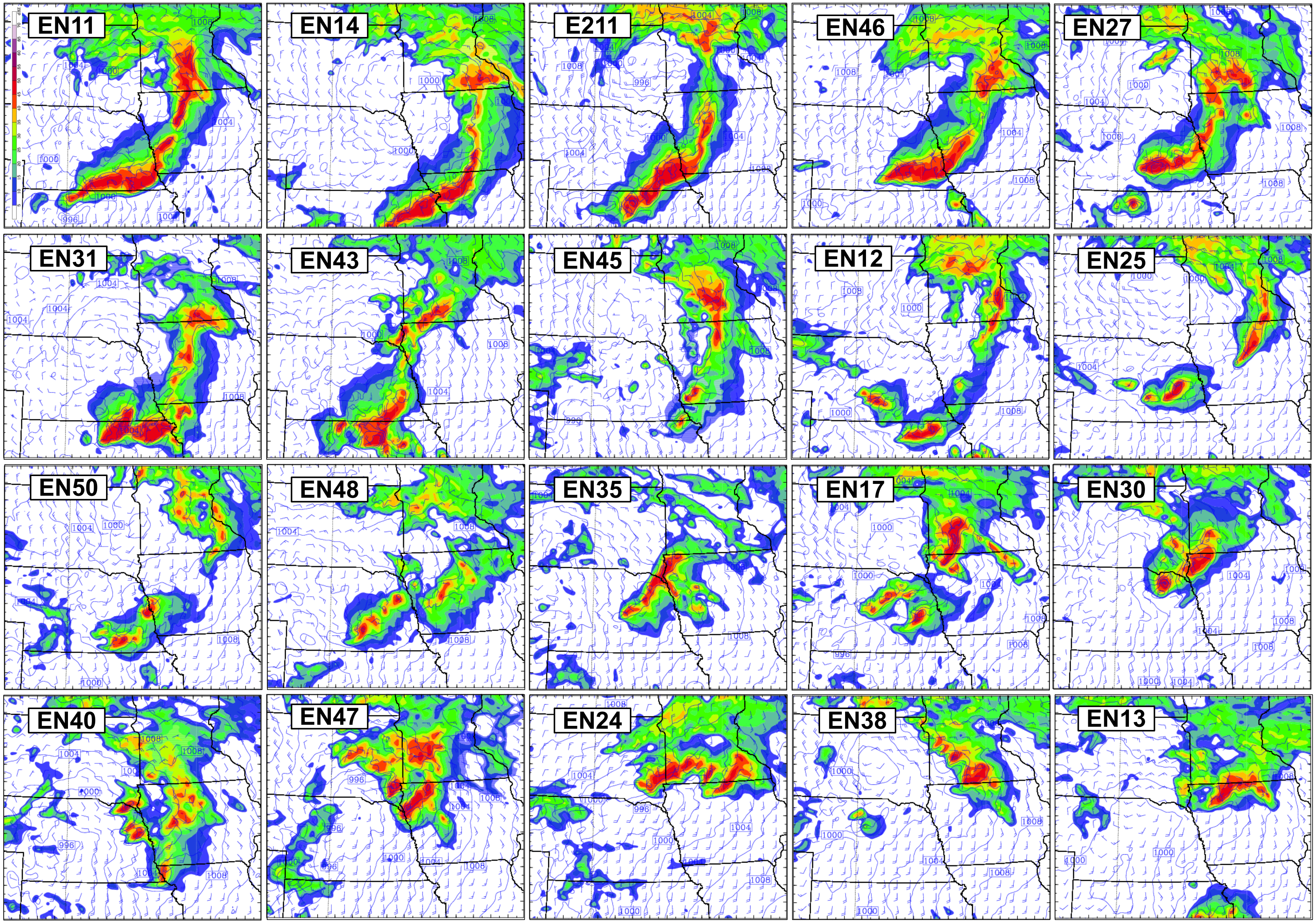
18h fcst from 3.3-km WRF ensemble simulations with EnKF perturbations



(Melhauser and Zhang 2012)

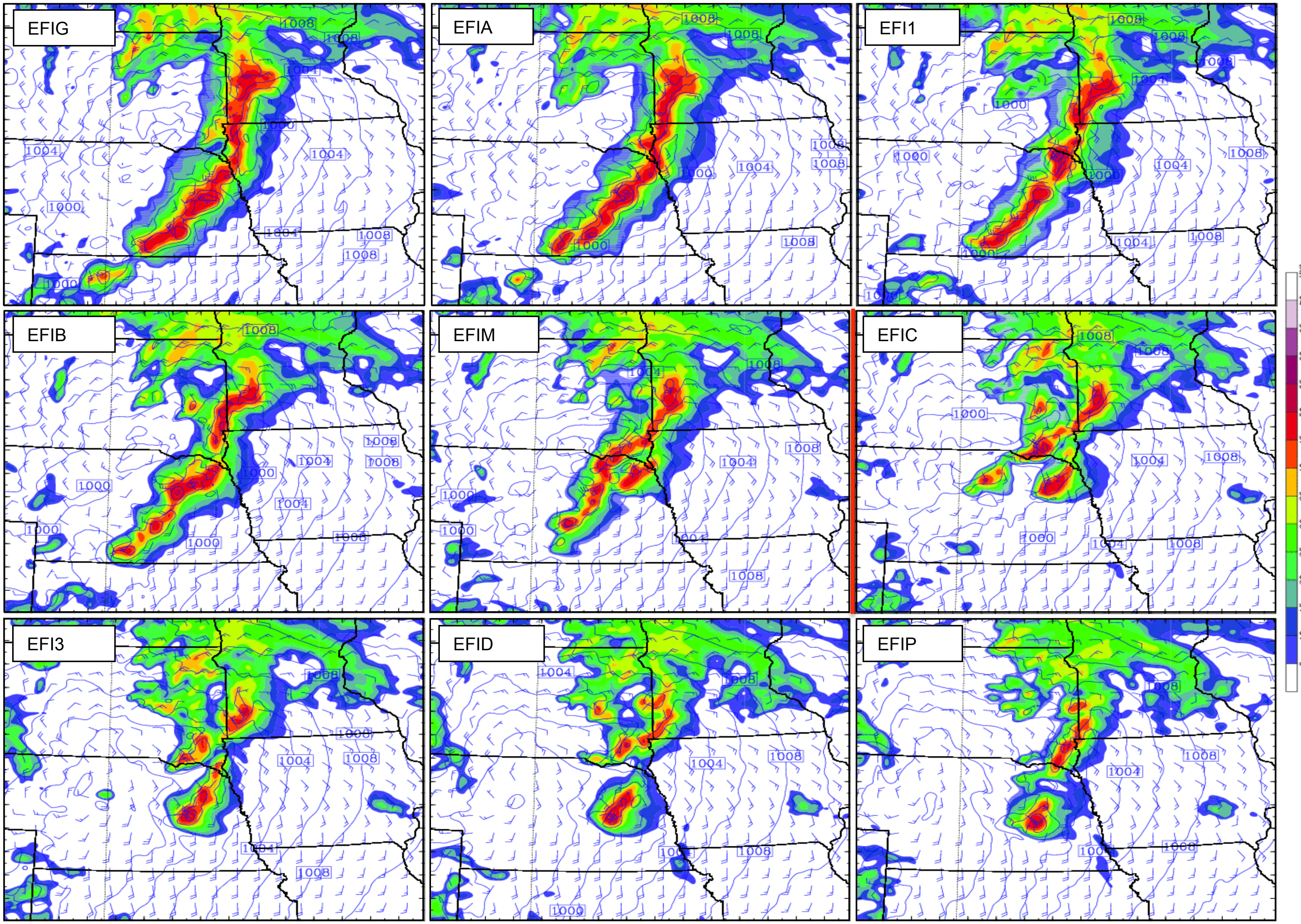
BAMEX: Ensemble Predictability of 10 Jun 2003 Bow Echo event

18h fcst from 3.3-km WRF ensemble simulations with EnKF perturbations

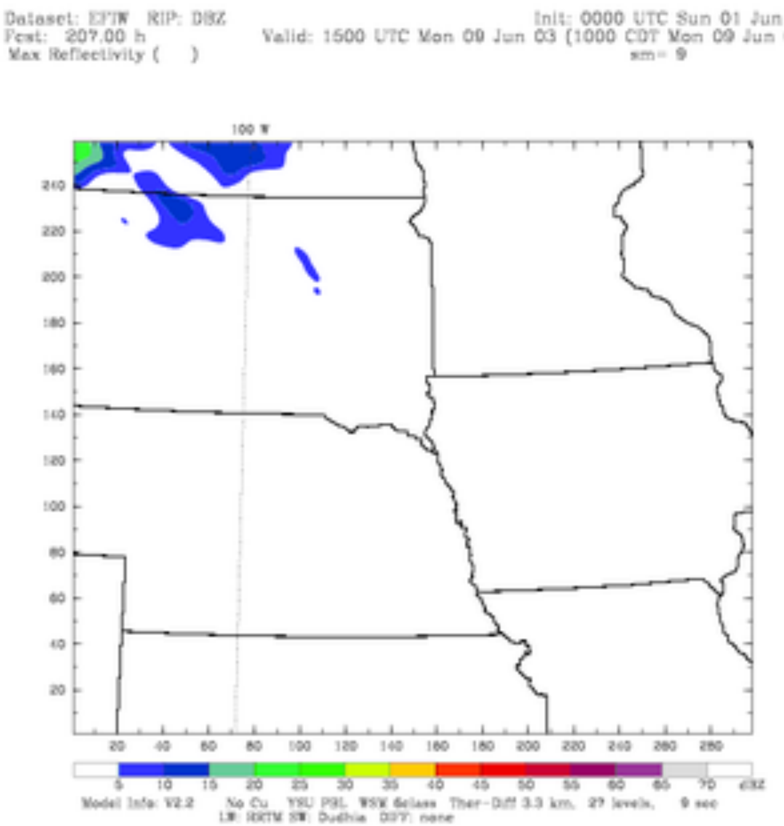


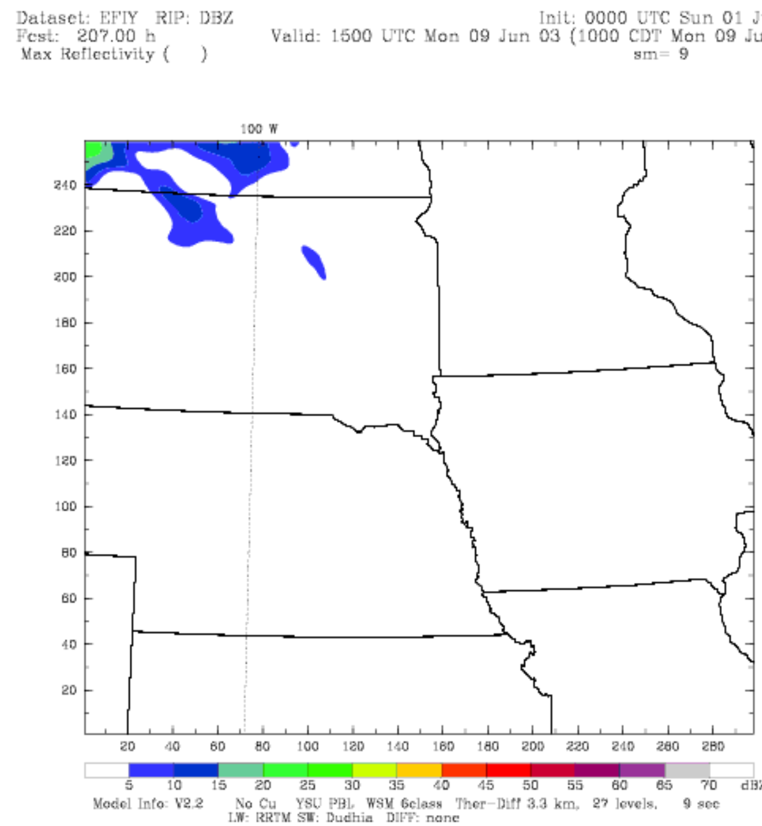
Predictability of 10 Jun 2003 Bow Echo event: Intrinsic limit?

Divide ICs difference between good and bad members by 8 and then 18h fcst



Forecast divergence with 1/8 of normal IC error

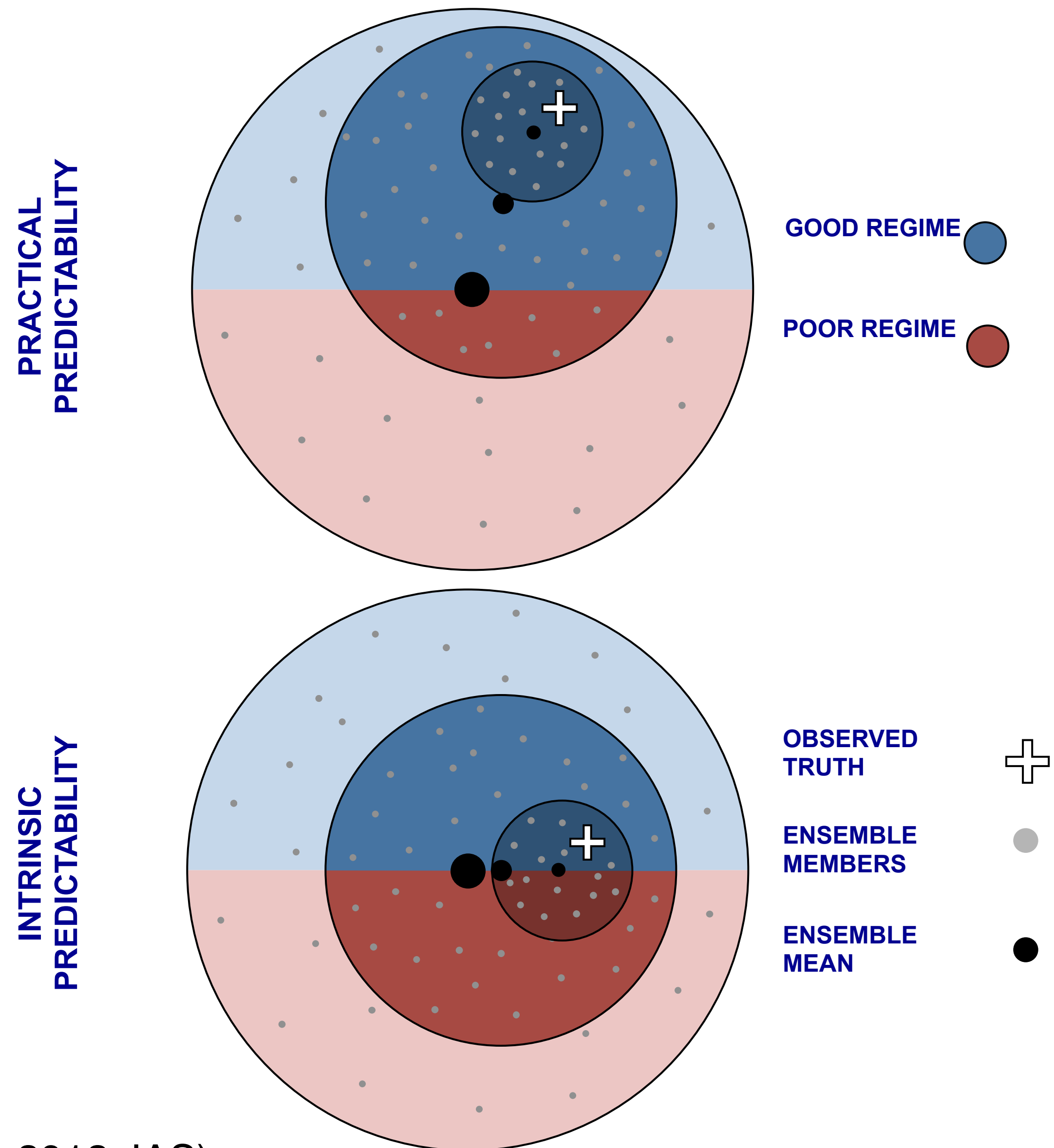




(Melhauser and Zhang 2012 JAS)

PRACTICAL vs. INTRINSIC PREDICTABILITY

- Where the members lie in relation to the truth and within which flow regime determines the evolution of that member
- If truth lies almost entirely in a flow regime
  - reducing the initial perturbations will hone in on the truth
  - increase the practical predictability of the event
- If truth lies near bifurcation
  - Reducing initial perturbations will contain both regimes/solutions
  - No increase in predictability
  - Intrinsic limit



(Melhauser and Zhang 2012 JAS)

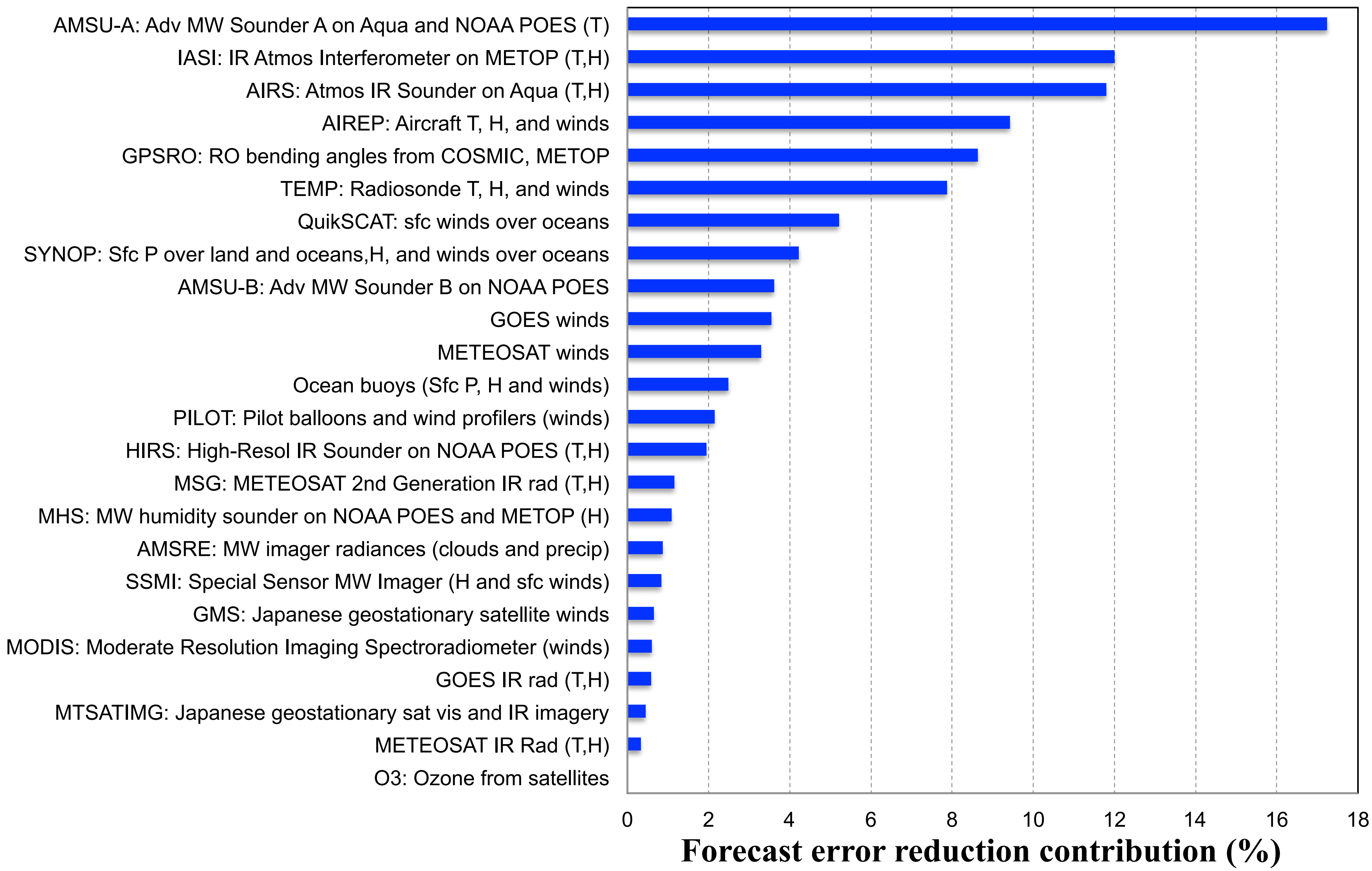
Why Ensemble Forecasts?—An Imperfect World

- Uncertainties in initial conditions due to data, background and DA
- Uncertainties in forecast models due to physics, resolution, numerics
- Intrinsic limit of predictability of weather/climate at different scales

How to Create An Ensemble?

- Multi-analysis Ics/BCs, multi-model, multi-physics, stochastic physics singular vectors, breeding, ensemble data assimilation (e.g., EnKF), …
- Key issues: Model vs. IC diversity, size vs. resolution, existing regional scale ensemble are mostly ad hoc in nature, predictability limits in terms of probabilistic versus deterministic, practical vs. intrinsic

Impacts of Different Observing Platforms on Global Medium-Range Weather Forecasts at ECMWF



Caveats: observation impacts are function of model; regional scale impacts unknown

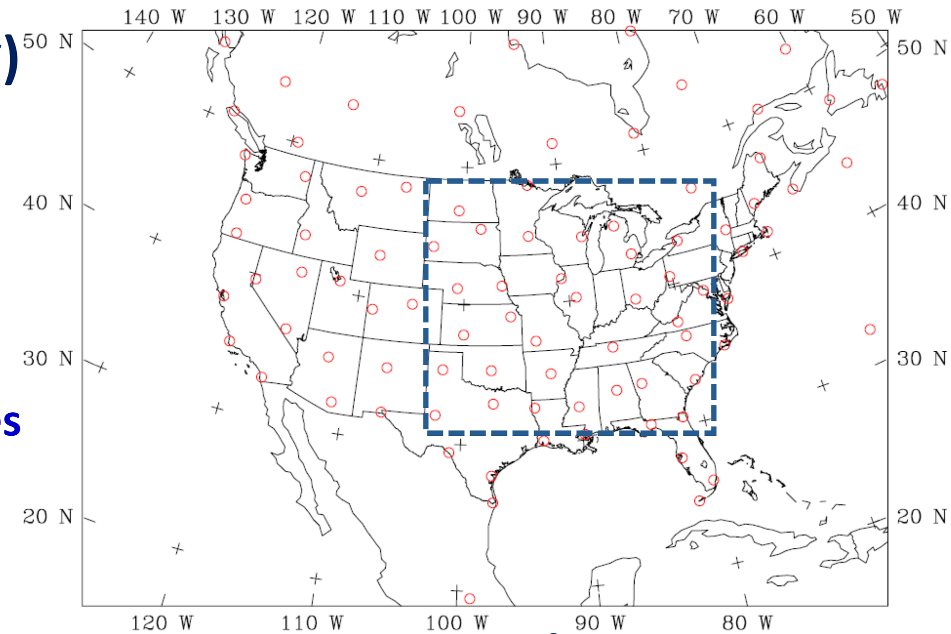
Issues in Satellite/radar Data for Regional Models

- How important is satellite data for regional scales? Mostly not used yet
- Satellite data coverage is irregular in time and space; existing quality control and bias correction procedures are developed for global models
- Usually the regional scale model top is too low for making full use of radiance observations
- Arguably the cloudy radiance (and radar reflectivity) is critical for mesoscale severe weather but the assimilation of cloudy radiance (and dBz) is still far from mature, even in global models
- Data archive, quality control and bias correction, observation operator for satellite (and radar) observations are usually not readily accessible to individual university PIs
- How can we do better under the auspice of BigData or EarthCube?

Comparison and coupling: DA Configurations over June 2003

- **WRF-ARW V3.1 (*Shamarock et al. 2005*)**
  90-km grids covering North America;
  27 vertical levels up to 50 hPa;
  LBCs interpolated from FNL analysis

- **EnKF (*Meng and Zhang 2008a, b*)**
  40-member ensemble with multi-schemes
  1800-km influence radius for localization
  0.8 relaxation and perturbed LBCs



- **3D/4D-Var of WRFDA V3.1 (*Barker et al. 2004; Huang et al. 2009*)**
  "NMC" background error covariance (B); Var-scale at 3.0 and Length-scale at 1.0
  6-h assimilation window (covering -3 to +3 h at every analysis time)

- **E4DVAR: coupling EnKF with 4D-Var (*Zhang et al. 2009*)**
  Perturbations are updated by EnKF, while mean is updated by 4D-Var
  Ensemble-based B is introduced into cost function via Alpha-control transform
  *(Lorenc 2003; Wang et al. 2007, 2008a, b***)**
  ensemble-B is localized with the influence radius of 1800-km
  ensemble-B and NMC-B are weighted at
  0.8 and 0.2, respectively

$$B = \frac{1}{\beta} B_{ens} + \left(1 - \frac{1}{\beta}\right) B_{nmc}, \quad (\beta = 1.25)$$

Strength and weakness of different DA methods

- ***3DVar:*** *Low computational cost, fit to observations*
  Lack of flow-dependent background uncertainty (B)

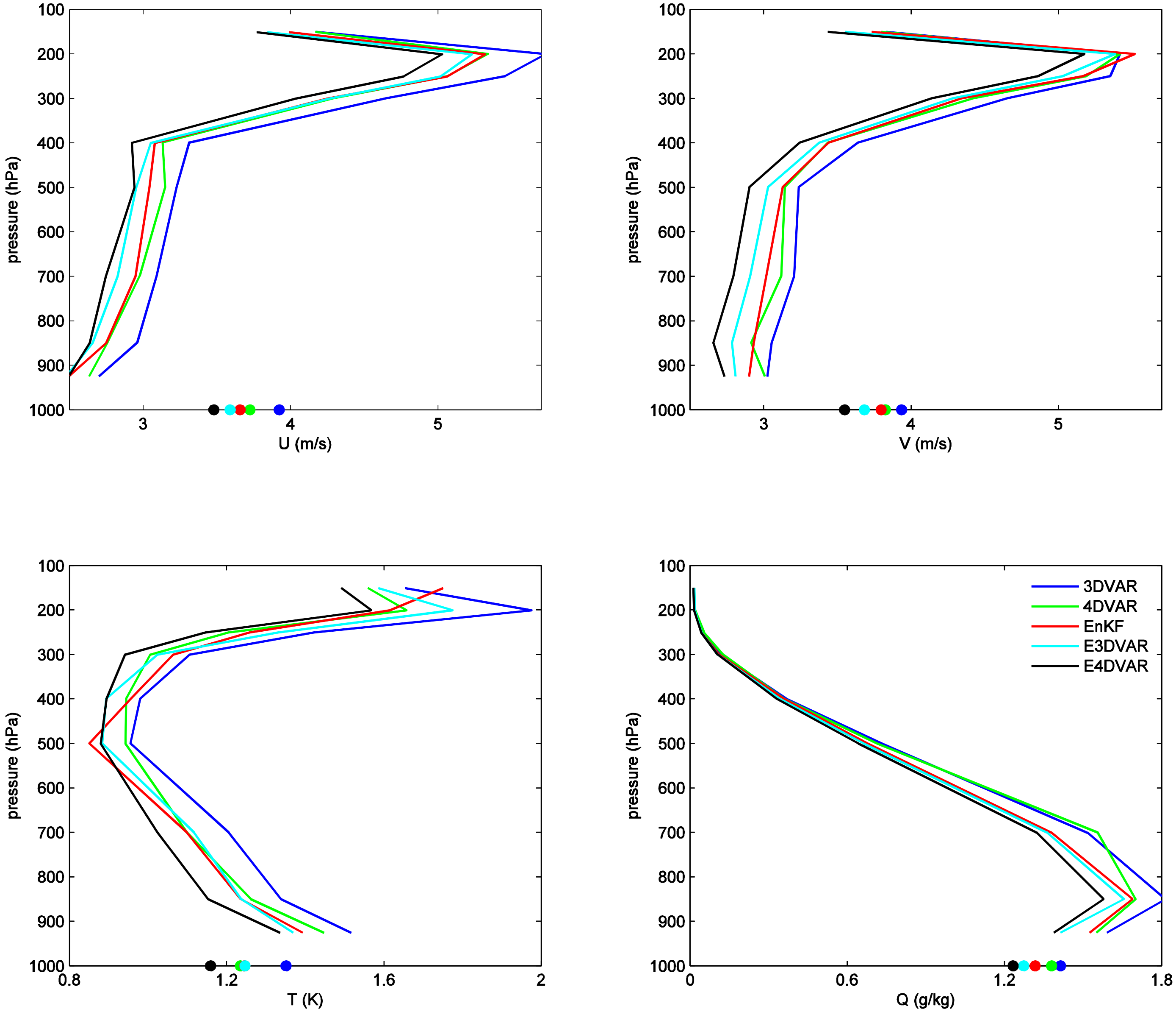
- ***4DVar:*** *Trajectory fitting for asynchronous observations*
  Poor background error covariance
  (but with some implicit flow dependence)
  High computational cost and high code maintenance

- ***EnKF:*** *Flow-dependent B; synergy with ensemble forecast*
  Moderate computational cost and low code maintenance
  Highly depends on the quality of
  ensembles and first-guess

- ***Hybrid:*** *coupling EnKF with 3D/4DVar*

Comparison of 3DVar, 4DVar, EnKF, E3DVar & E4DVar

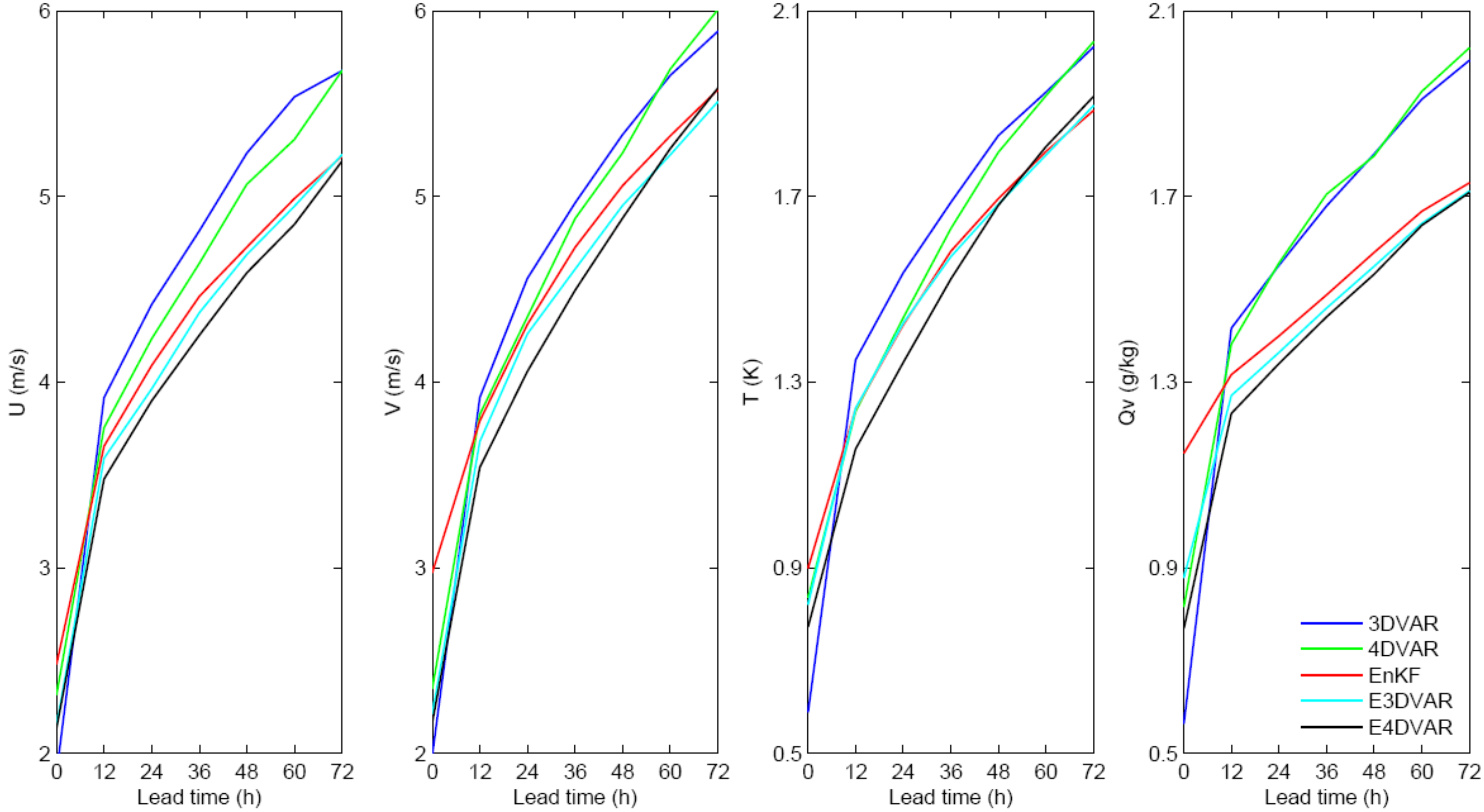
Mean vertical profiles of month-averaged 12-h forecast RMSE



(Zhang et al. 2011, 2012 MWR; Zhang and Zhang 2012 MWR)

Comparison of 3DVar, 4DVar, EnKF, E3DVar & E4DVar

0-72hr U, V, T & Q RMS forecast error over CONUS Jun 2003 (60 runs)



(Zhang et al. 2011, 2012 MWR; Zhang and Zhang 2012 MWR)

Mesoscale EnKF: Key Issues and Challenges

- **Model error**
  - Covariance inflation or additive noise, going adaptive
  - Multi-physics ensemble; parameter perturbation within one parameterization?
  - Shall we go for multi-model ensemble? Incompatible state elements
- **Sampling error**
  - Covariance localization: wide open in terms of optimality, balance issues
  - Localization for multiscales: Adaptive localization, Successive localization
- **Hybrid with VAR: are there real advantages?**
  - Useful in model error treatment; sampling error, non local obs localization, balance, time-integrated observations, …
- **Computational considerations**
  - ensemble size, resolution, parallelization; do we need and can we afford adjoint?

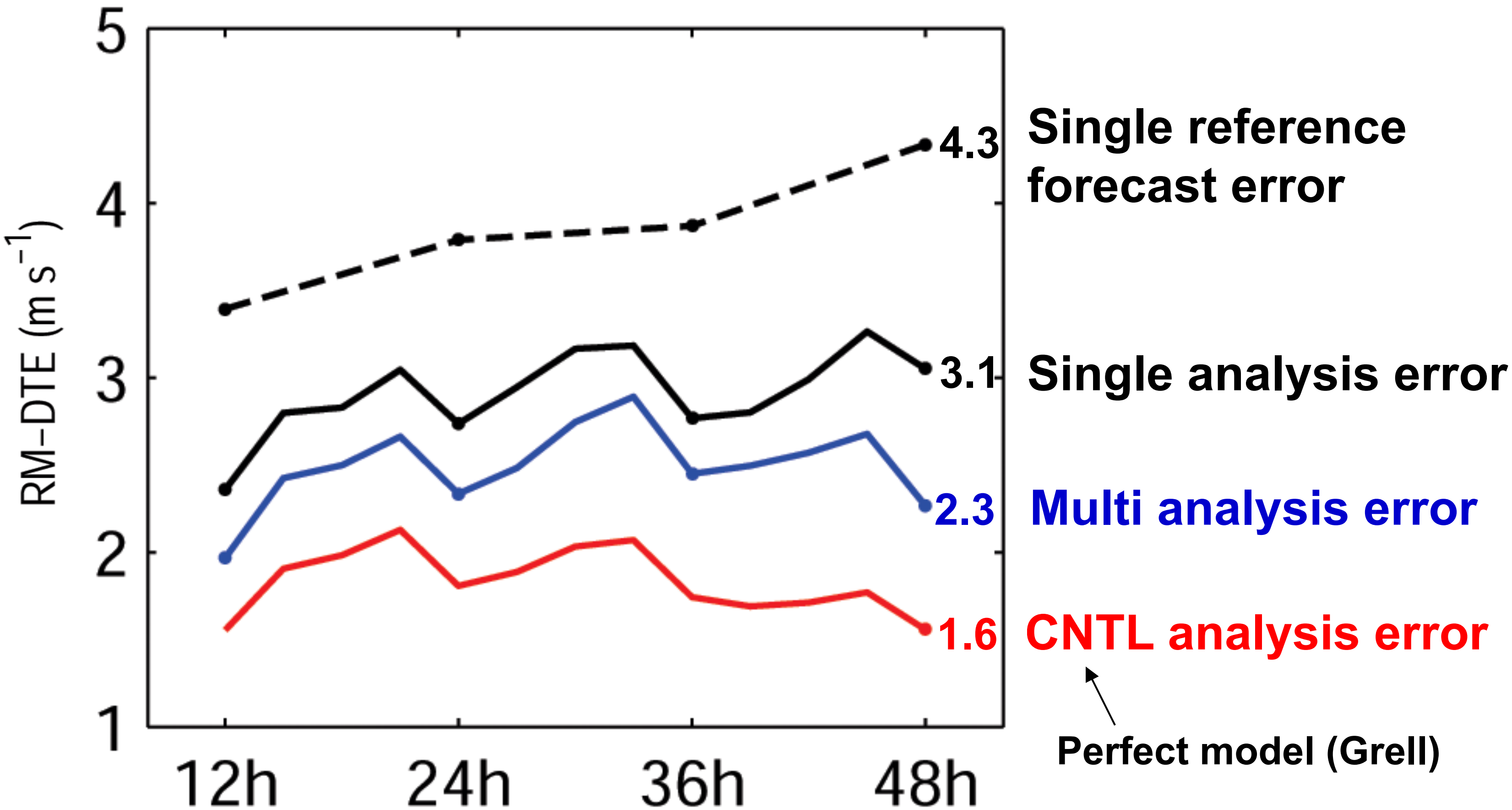
Model Error --- bottleneck for all NWP issues

- Resolved vs. subgrid-scale: synergy between parameterizations, partially resolved physics, column-based only, …
- Parametric versus stochastic physic uncertainty: can parameter estimation lead to better physics parameterizations?
- Multi-model/multiphysics: how many models we need/afford? How much diversity of physics parameterizations is too much?
- Stochastic schemes in global models: Stochastically-perturbed physics tendencies, energy backscattering, vorticity confinement, stochastically-perturbed boundary-layer humidity, …
- Can we represent physics diversity and model error with parametric + stochastic errors within a single model/physics?

Model Error in EnKF: Multi-physics imperfect-model OSSE

Single-scheme: KF used for the ensemble

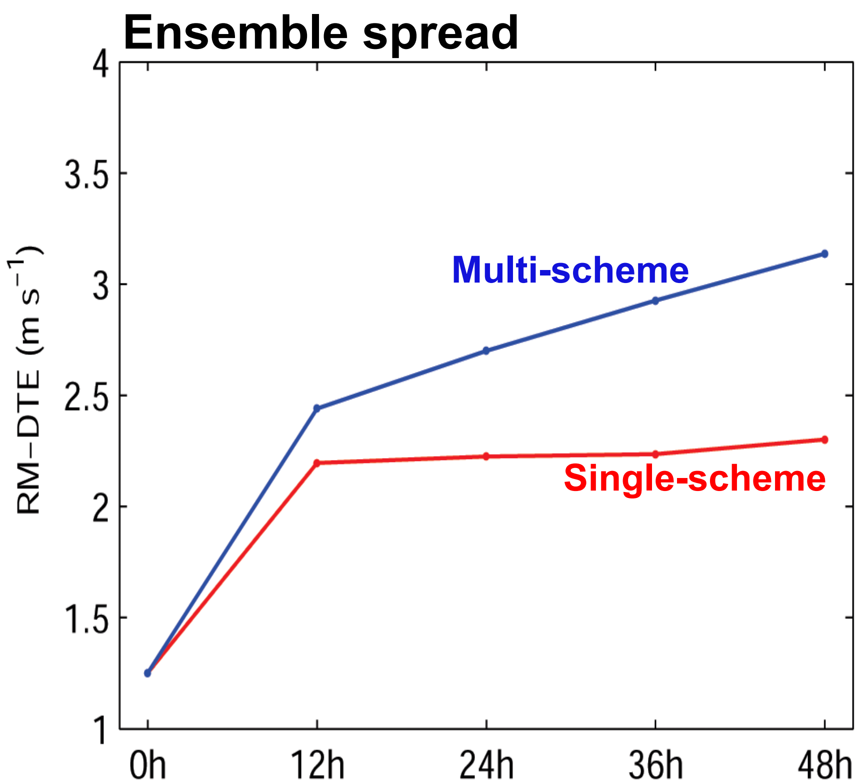
Multi-scheme: KF2, KF, BM, and KUO used for the ensemble

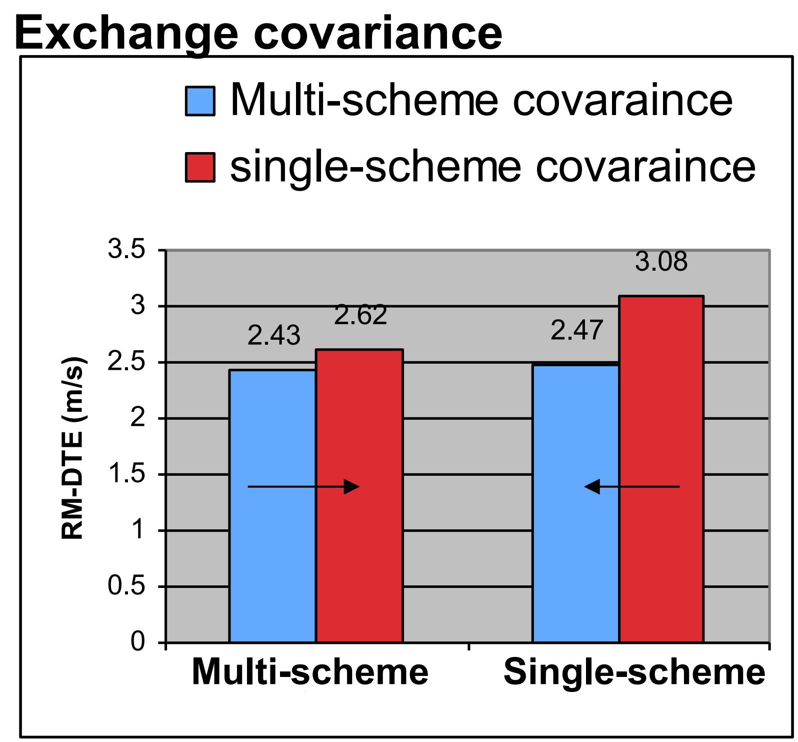


Multi-scheme has smaller analysis error than that of single scheme

(Meng and Zhang 2007 MWR)

Model Error in EnKF: Why multi-scheme is better?



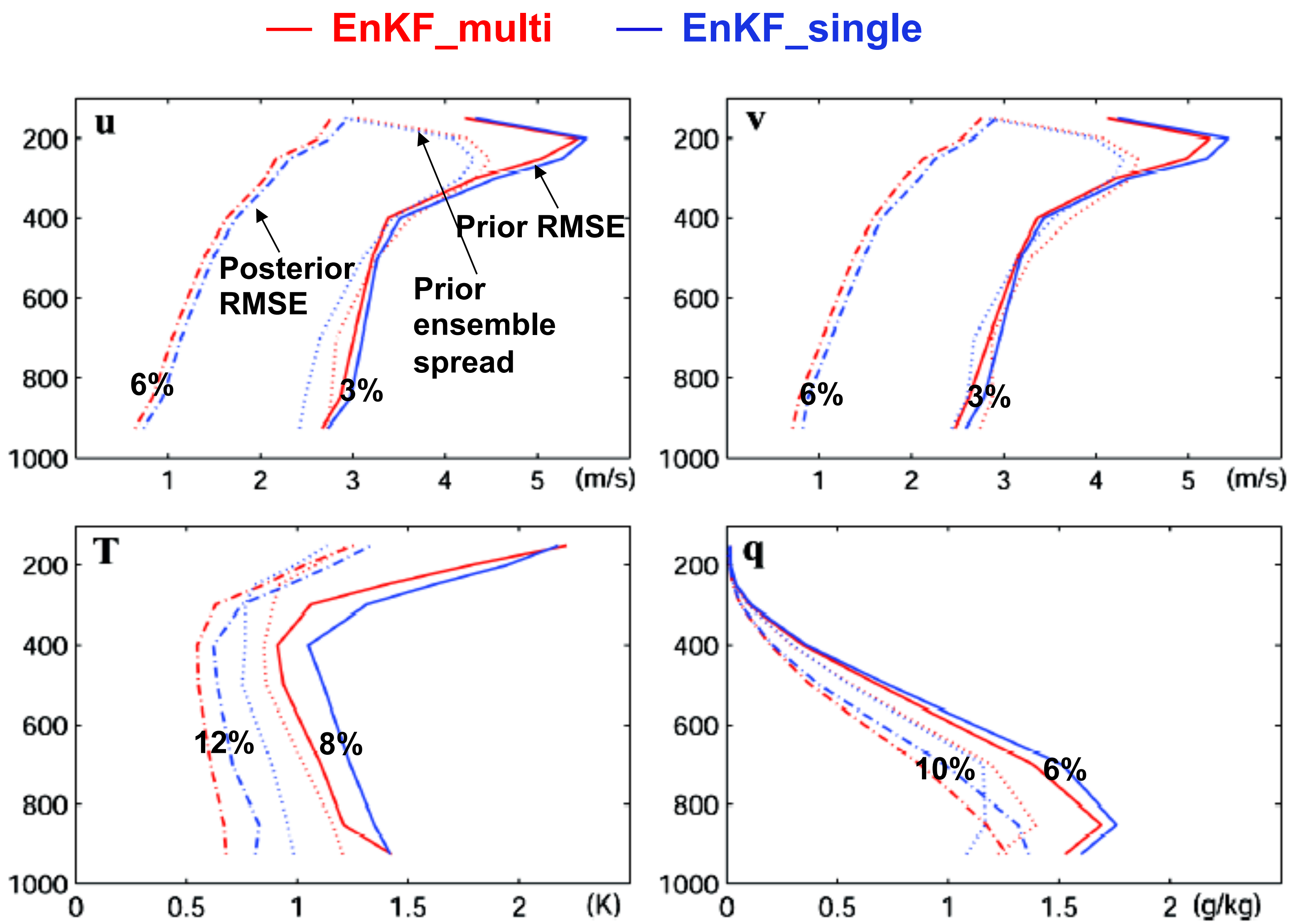


Multi-scheme is less vulnerable to filter divergence due to larger ensemble spread

Multi-scheme has a better background error covariance structure

(Meng and Zhang 2007 MWR)

EnKF with real obs: Month-long Multi- vs. Single-scheme



Multi-scheme works consistently better than single scheme esp. in T and q

(Meng and Zhang 2008a,b MWR)

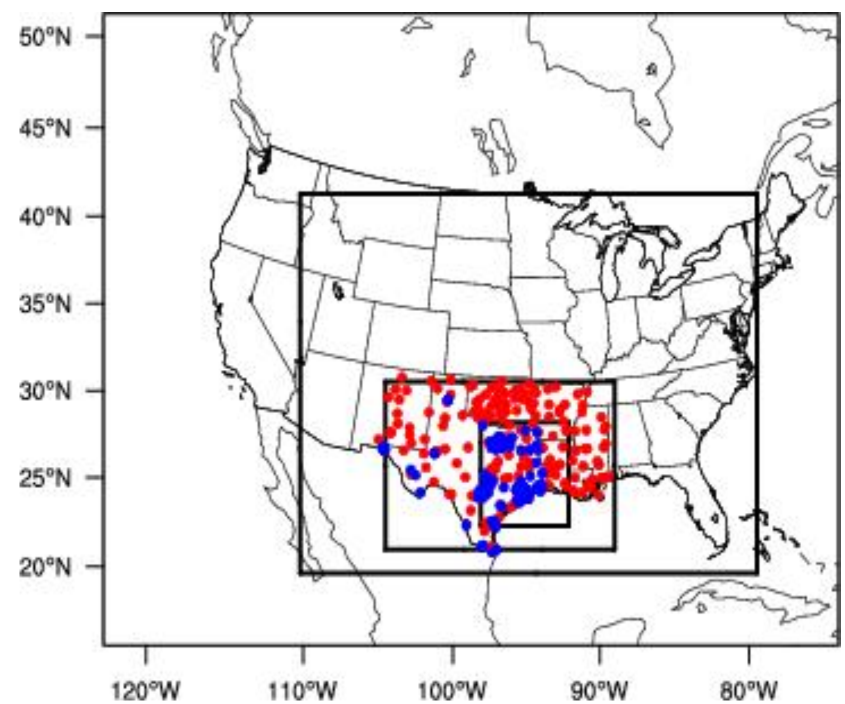
WRF sensitivity to PBL schemes

Episode & Resolution

- Period: July – Sept., 2005 (TexAQSII)
- Resolution: 108km, 36km, 12km, 4km
- Grids: 53×43, 97×76, 145×100, 166×184

Model Configurations

- YSU, ACM2, MYJ PBL schemes
- WSM 6-class graupel scheme
- NOAH land-surface model (LSM)
- Dudhia short wave radiation
- RRTM long wave radiation
- Grell-Devenyi ensemble cumulus scheme



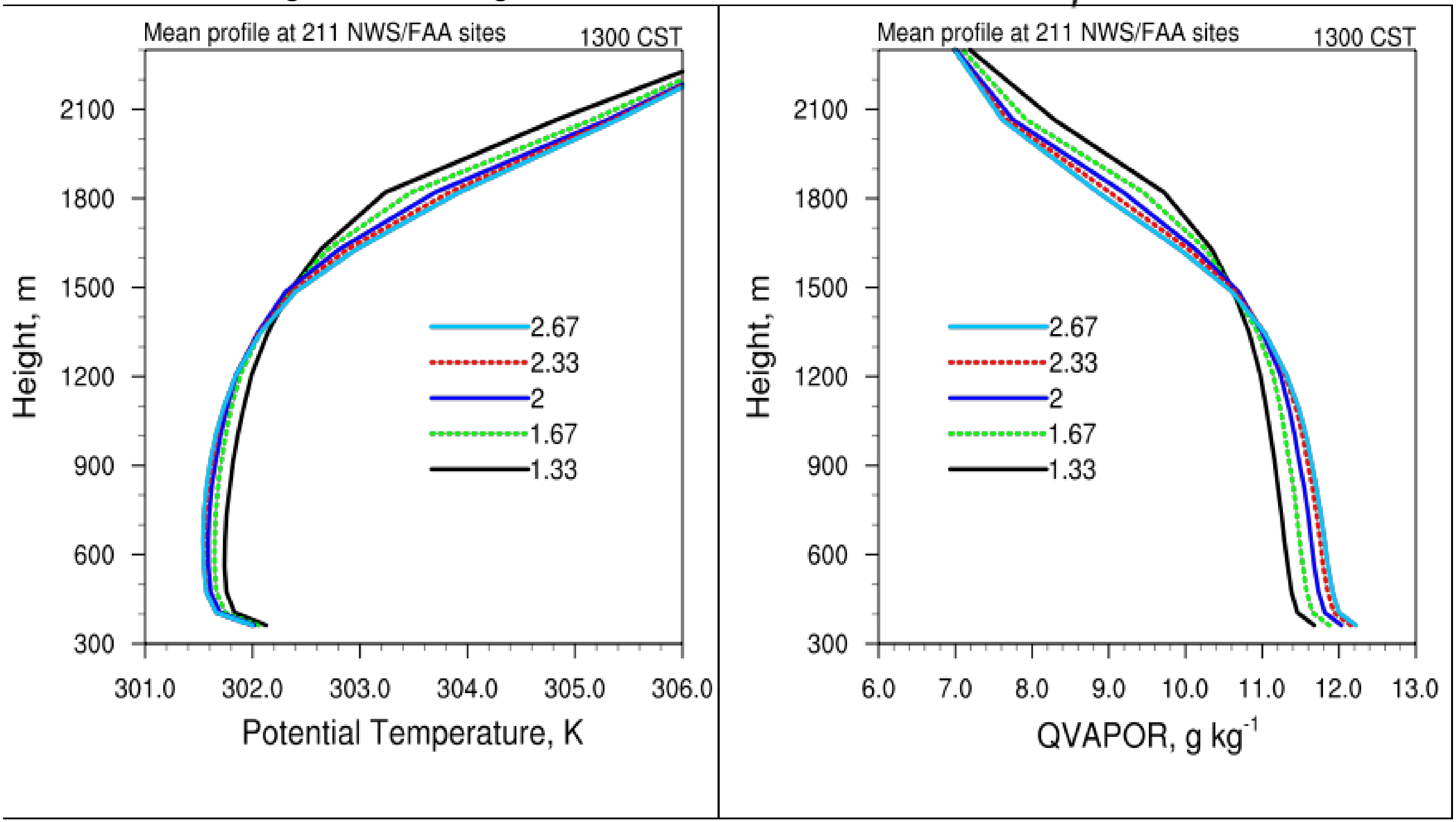
Domains and TCEQ, NWS/FAA sites

(Hu et al. 2010a JAMC)

Physics Uncertainty: *sensitivity to p in ACM2 PBL*

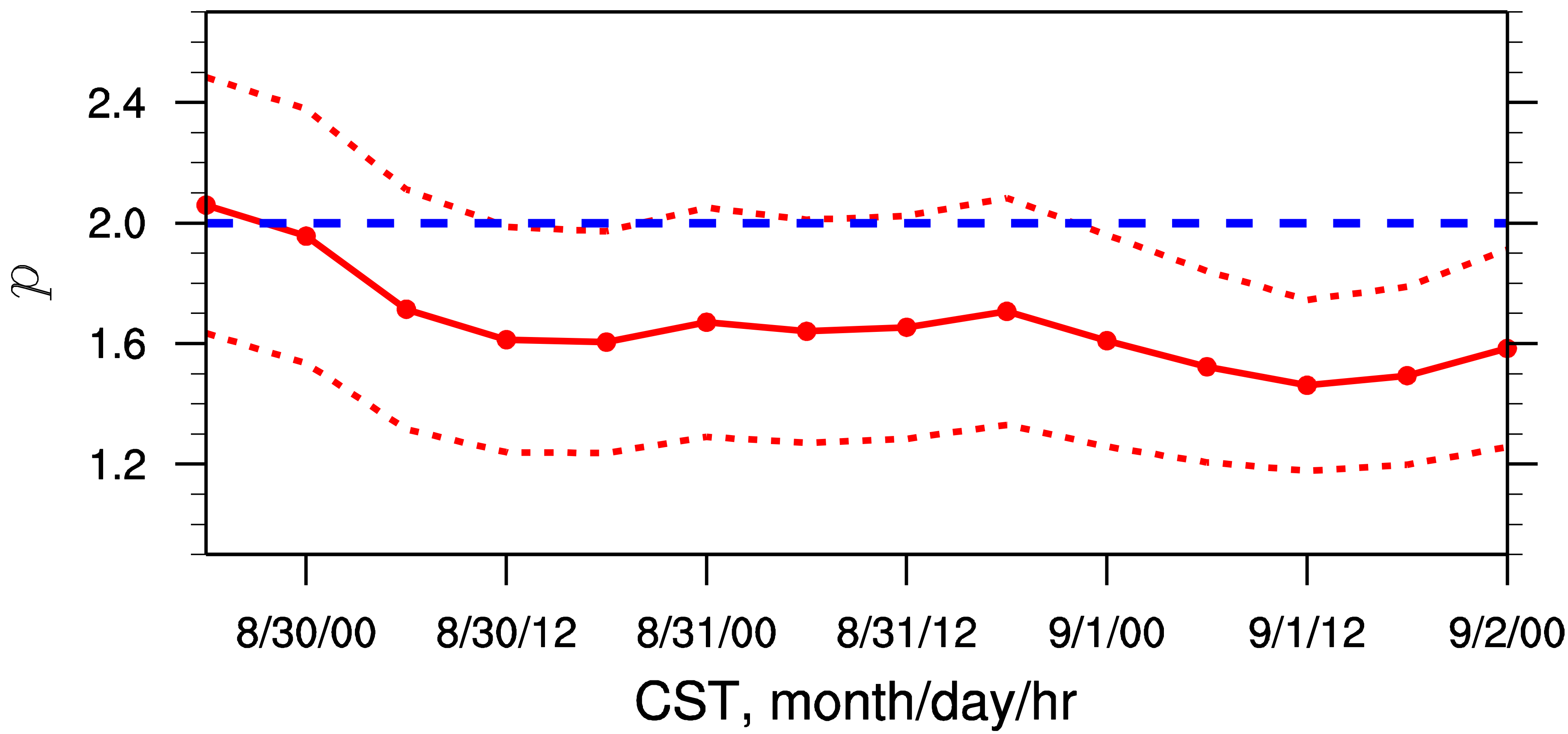
Lower p => stronger vertical mixing
=> higher PBL height

$$K_z(z) = k\frac{u_*}{\phi}z(1 - z/h)^p$$



(Nielsen-Gammon et al. 2010 MWR; Hu et al. 2010a JAMC, 2010b GRL)

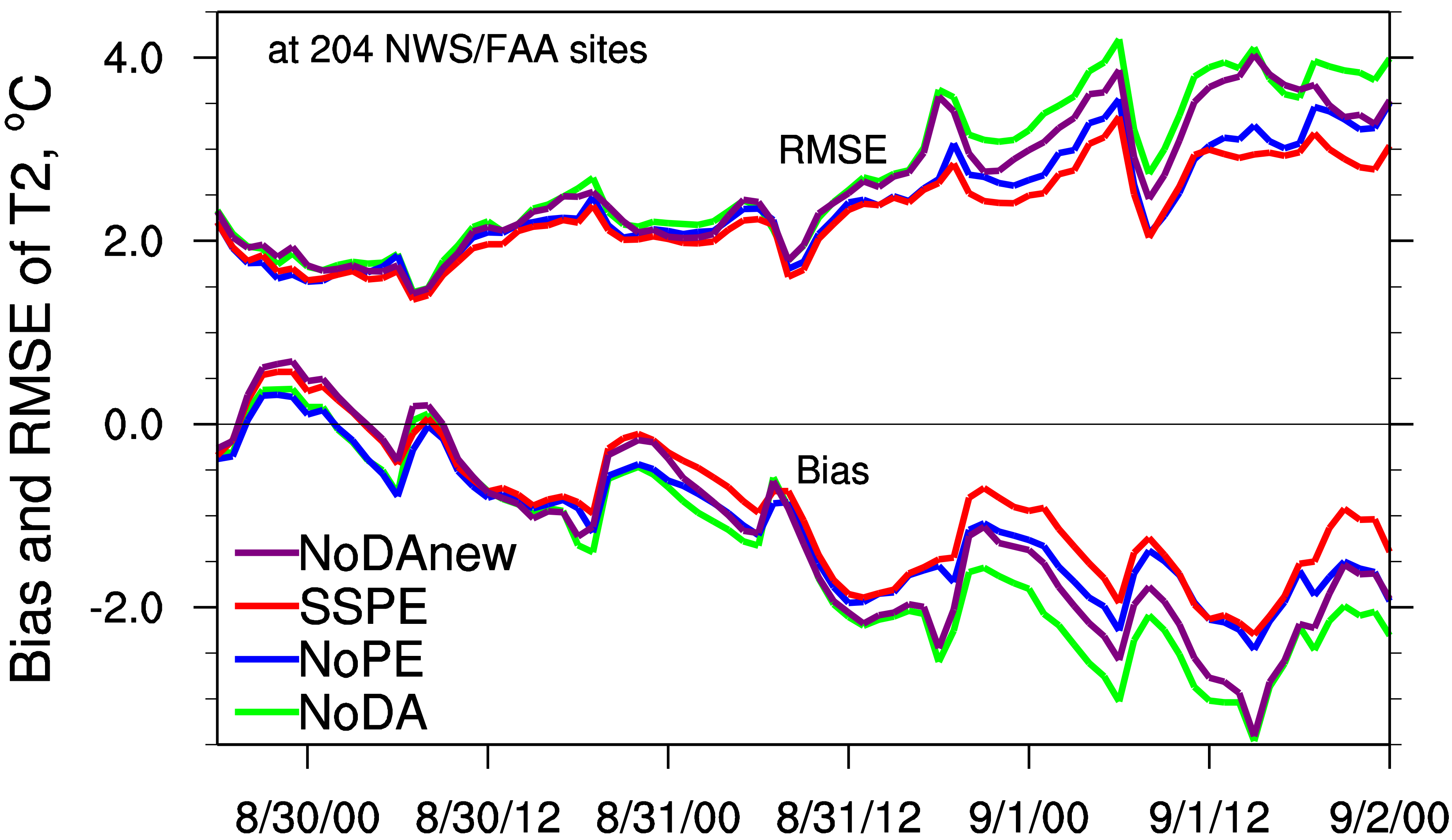
Model error treatment through simultaneous state and parameter estimation (SSPE) of *p* with EnKF



During most of time, SSPE predicts *p* value lower than 2.0 (default).

(Hu et al. 2010b GRL)

WRF forecast bias and error of T2 w/ and w/o SSPE



SSPE predicts the least cold bias.

(Hu et al. 2010b GRL)

Science Challenges in Regional DA and EF

- Observations: RAOBS, SFCOBS, Mesonets, Radar, Satellite, GPS RO
    - Data archive/access, quality control/bias correction, obs operator
- Forecast models: WRF-ARW, WRF-NMM, COAMPS, ARPS, MPAS
    - Physics uncertainty, stochastic/parametric error, resolution, BCs
- DA methods: 3DVAR, 4DVAR, EnKF, hybrids, (nudging, global DA)
    - Ensemble/adjoint, Static/ensemble B, model error, learning curve
- EF methods: multi-analysis ICs, multi-model/physics, EnKF, breeding
    - Model vs. IC diversity, size vs. resolution, most ad hoc in nature
- Predictability: global vs. regional vs. storm-scale, deterministic vs. probabilistic, practical vs. intrinsic limits, …

Community-shared Regional DA and EF
Some initial thoughts on science needs

- Data hub (Unidata?) for quality controlled observations, selected model output, shared data mining, verification and visualization
- Shared forecast domain (CONUS?) and performance metrics (QPF?)
- Baseline or reference modeling system: well-configured forecast model (WRF?) with well-tuned DA schemes (WRFVAR or DART or GFS)
- Advanced theme-based research foci, instead of simple multiplication
    - Observations: obs operator, quality control, bias correction, …
    - Model physics: microphysics, PBL, LSM, radiation, …
    - DA methods: 3DVAR, 4DVAR, EnKF, hybrids, …
    - EF methods: model vs. IC diversity, size vs. resolution, multi-model/physics/analyis, stochastic physics, EnKF, breeding, SVs, …