RECENT DEVELOPMENTS, CURRENT STATUS & PLANS FOR THE NCEP ENSEMBLE FORECAST SYSTEMS

Zoltan Toth

Environmental Modeling Center
NOAA/NWS/NCEP

Acknowledgements:
Yuejian Zhu, Jun Du, Mozheng Wei, Dingchen Hou, Bo Cui, Malaquias Pena, Louis Uccellini, Steve Lord, Roman Krzysztofowicz

http://wwwt.emc.ncep.noaa.gov/gmb/ens/index.html

OUTLINE / SUMMARY

- OBJECTIVE OF ENSEMBLE FORECASTING
  - GENERATE FINITE SAMPLE OF PLAUSIBLE SOLUTIONS
- NCEP ENSEMBLE FORECAST SYSTEMS
  - SEASONAL
  - GLOBAL
  - REGIONAL
  - HIGH IMPACT
- COMPONENTS OF ENSEMBLE FORECASTING
  - INITIAL PERTURBATIONS
    - Interface with DA
  - MODEL-RELATED PERTURBATIONS
    - Interface with numerical modeling
  - STATISTICAL CORRECTIONS
    - Bias correction – Correcting lead time dependent systematic errors
    - Downscaling – No forecasting involved
  - APPLICATIONS
    - Decision Support Systems

OBJECTIVE OF ENSEMBLE FORECASTING

- Background
  - Direct computation of analytical / continuous forecast pdf not achievable
    - Louiville eqs. excessively expensive

- Substitute goal
  - Generate finite sample of solutions representing underlying forecast pdf
    - Likelihood of solutions (equal or not equal) must be known to estimate pdf
  - Constraints
    - Maximize statistical resolution
      - Narrow pdf as much as possible while maintaining
    - Provide good statistical reliability
      - Realism/fidelity of solutions AND/OR
      - Statistical corrections

WHAT'S NEEDED TO ACHIEVE GOAL?

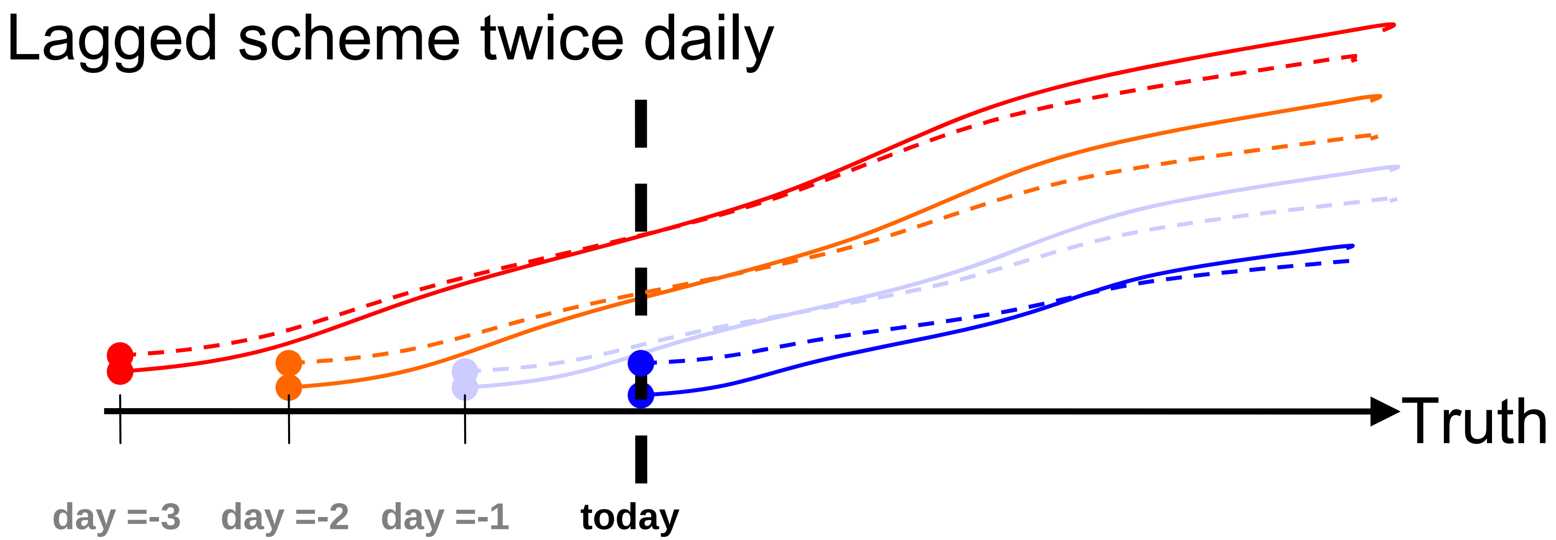
- Estimate & sample initial pdf
  - Dynamically conditioned perturbations
    - Link with DA
- Represent model related uncertainty
  - Consider each model component
    - Link with numerical modeling
- Statistically correct ensemble output
  - Remove lead-time dependent bias
    - How large sample do we need?
  - Downscale bias-corrected forecasts
    - Relationship between high & low-res analysis fields OR
    - LAM
- Apply statistically corrected ensemble output
  - Inter / extrapolate ensemble data for continuous pdf
  - Drive downstream applications with ensemble trajectories

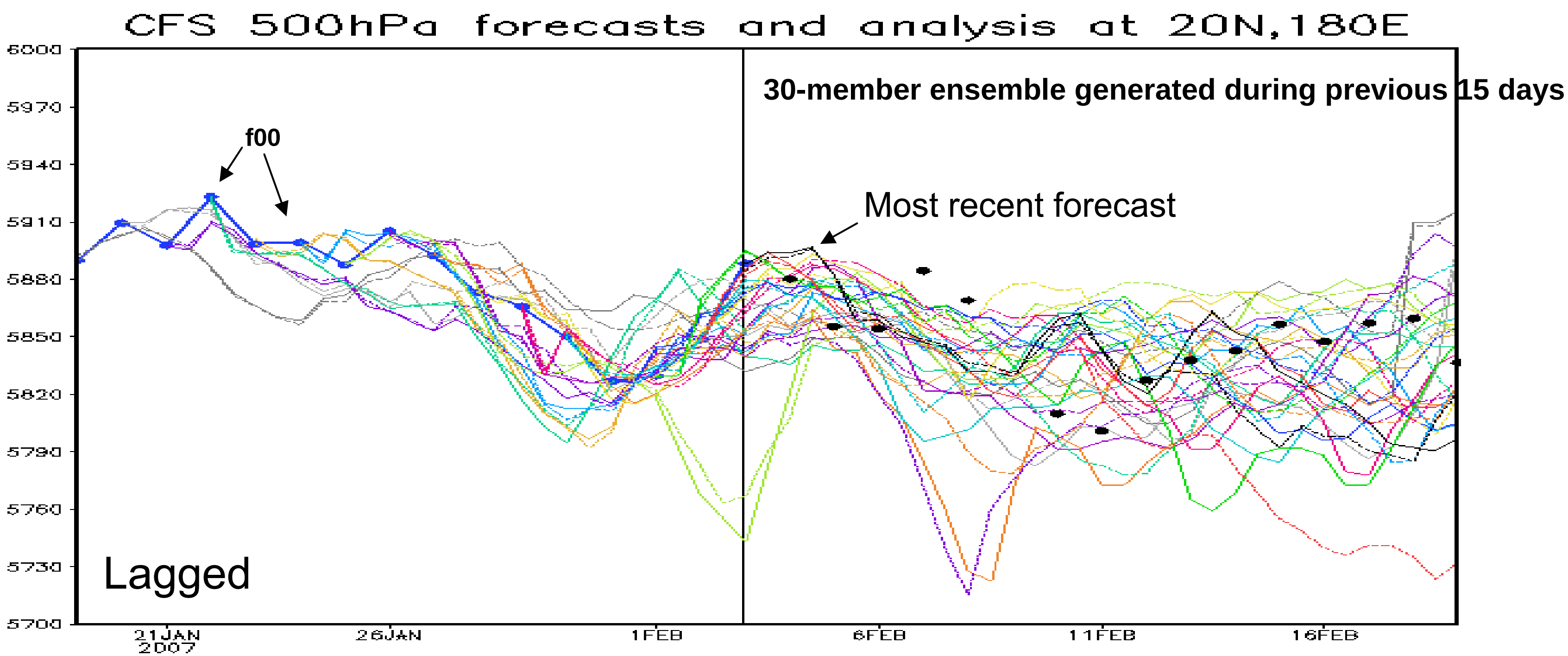
NCEP ENSEMBLE SYSTEMS – NOV. 2007

SYSTEM / COMPONENT	SEASONAL	GLOBAL	REGIONAL	HIGH IMPACT (Under design)
Model	GFS+MOM3 Coupled model	GFS	ETA (10), RSM (5), WRF(2*3)	Relocatable WRF
Initial uncertainty	*Lagged*	*ET with Rescaling*	*Breeding*	*?*
Boundary perturbations	*None*	*Fixed SST*	*From global ensemble*	*From regional ensemble*
Model diversity	None	None	Mult. conv. schemes	Yes
Stochastic physics	None	None (Planned)	None	?
Tropic. storm spec.	None	Relocation	None	Hurricane WRF
Schedule	Twice/day	00, 06, 12, 18 UTC	03, 09, 15, 21 12UTC	On demand
Spatial resolution / Output freq.	T62L64 (atm), 1/3-1 deg (ocean), daily	T126L28 (d0-d16) ~90km 6, hrly	32-45 km, 3 hrly	5-10 km, 1 hrly
Control member(s)	Yes	Yes (hi-lo)	Yes (5)	Yes
Perturbed members	Lagged	20	16+5	?
Forecast length	10 mos	16 days (384 hours)	87 hrs	6-12 hrs
Post-processing	Based on 25 yrs hindcasts	Bias correction (Recursive filter, all members)	Bias correction (Recursive filter, each member	?
Implementation	2004	March 27th 2007	Nov. 2007	2010?

Thurs. talk

NCEP CLIMATE FORECAST SYSTEM (CFS)

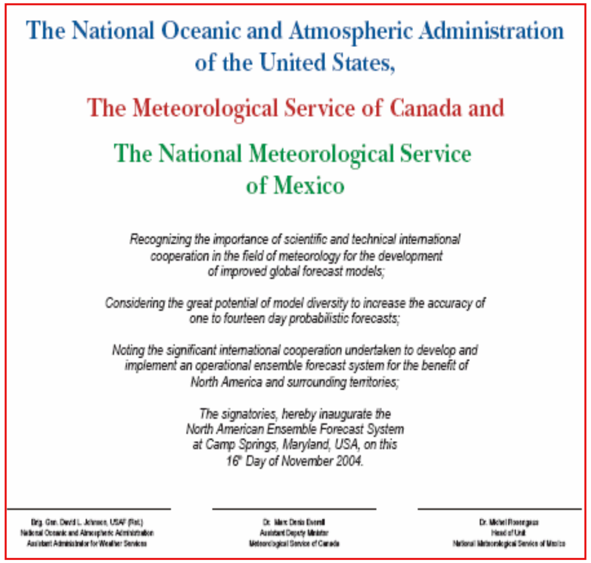




NORTH AMERICAN ENSEMBLE FORECAST SYSTEM

International project to produce operational multi-center ensemble products

- Combines global ensemble forecasts from Canada & USA
  - 40 members per cycle, 2 cycles per day from MSC & NWS
    - 6-hourly output frequency
    - Forecasts out to 16 days
- Generates products for
  - Weather forecasters
    - E.g., NCEP Service Centers (US NWS)
  - Specialized users
    - E.g., hydrologic applications in all three countries
  - End users
    - E.g., forecasts for public distribution in Canada (MSC) and Mexico (NMSM)
- Operational outlet for THORPEX research using TIGGE archive
  - Prototype ensemble component of THORPEX Global Interactive Forecast System (GIFS)



The National Oceanic and Atmospheric Administration of the United States,

The Meteorological Service of Canada and

The National Meteorological Service of Mexico

Recognizing the importance of scientific and technical international cooperation in the field of meteorology for the development of improved global forecast models;

Considering the great potential of model diversity to increase the accuracy of one to fourteen day probabilistic forecasts;

Noting the significant international cooperation undertaken to develop and implement an operational ensemble forecast system for the benefit of North America and surrounding territories;

The signatories, hereby inaugurate the North American Ensemble Forecast System at Camp Springs, Maryland, USA, on this 16th Day of November 2004.

Brig. Gen. David L. Johnson, USAF (Ret.) National Oceanic and Atmospheric Administration Assistant Administrator for Weather Services	Dr. Marc Denis Everell Assistant Deputy Minister Meteorological Service of Canada	Dr. Michel Rosengaus Head of Unit National Meteorological Service of Mexico

NAEFS CONFIGURATION

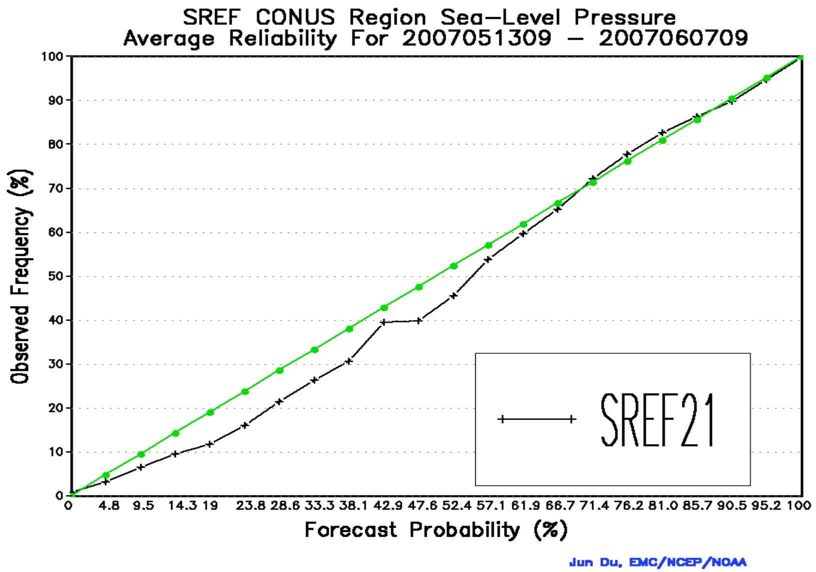
July 2007

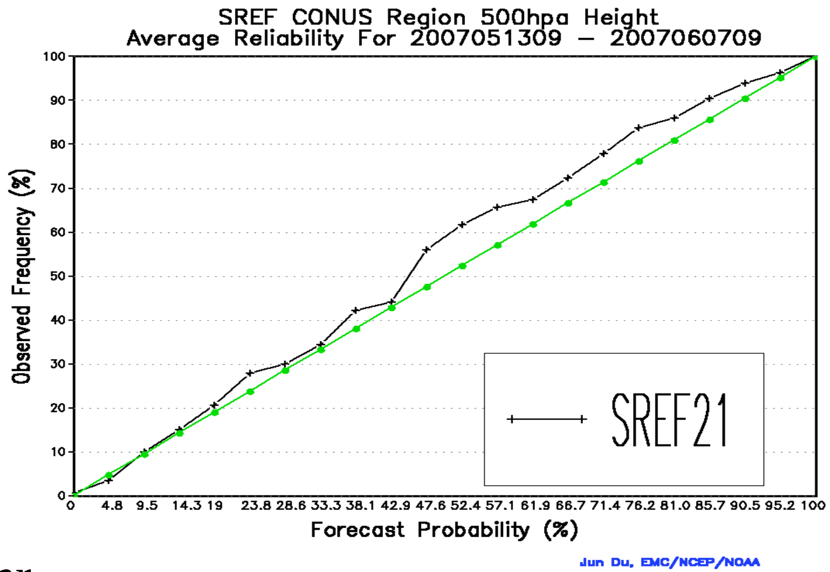
	NCEP	**CMC**
Model	GFS	GEM
Initial uncertainty	*ET with Rescaling*	*EnKF*
Model diversity	None	Yes
Stochastic physics	None (Planned)	Yes
Tropical storm specif.	Relocation	None
Daily frequency	00, 06, 12, 18 UTC	00 and 12UTC
Resolution	T126L28 (d0-d16) ~90km	(d0-d16) ~1.0degree
Control	Yes	Yes
Ensemble members	20 for each cycle	20 for each cycle
Forecast length	16 days (384 hours)	16 days (384 hours)
Post-process	Bias correction for ensemble mean	Bias correction for each member
Last implementation	March 27th 2007	July 10th 2007

Yuejian Zhu

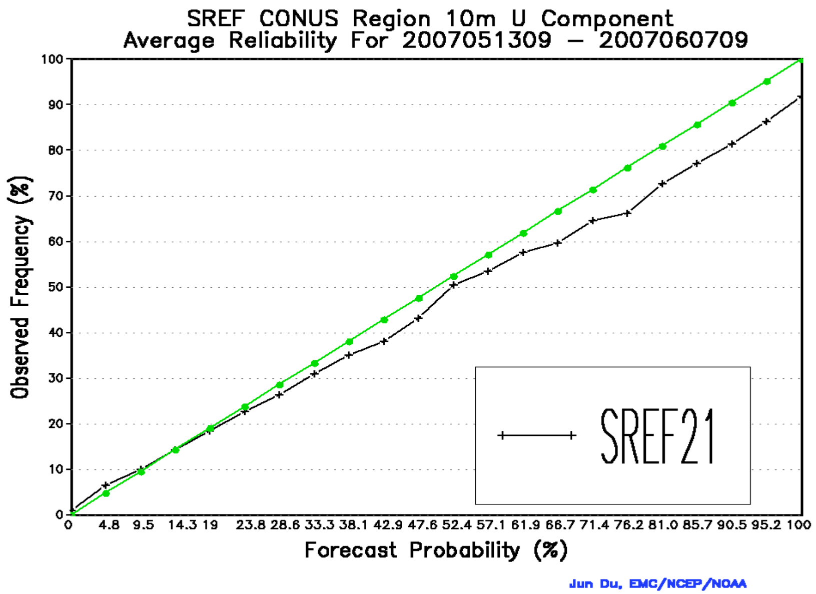
Reliability of SREF21-based Probabilistic Forecasts

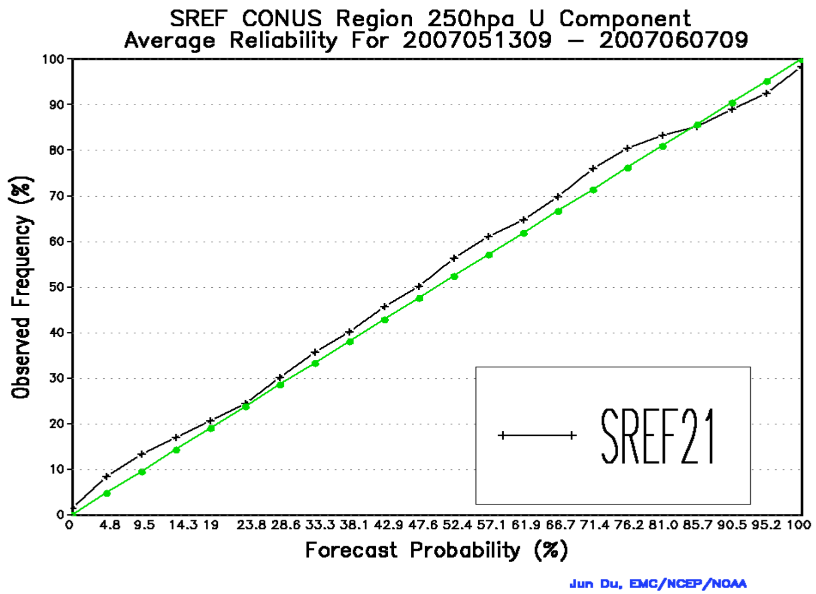
Jun Du





At 45hr

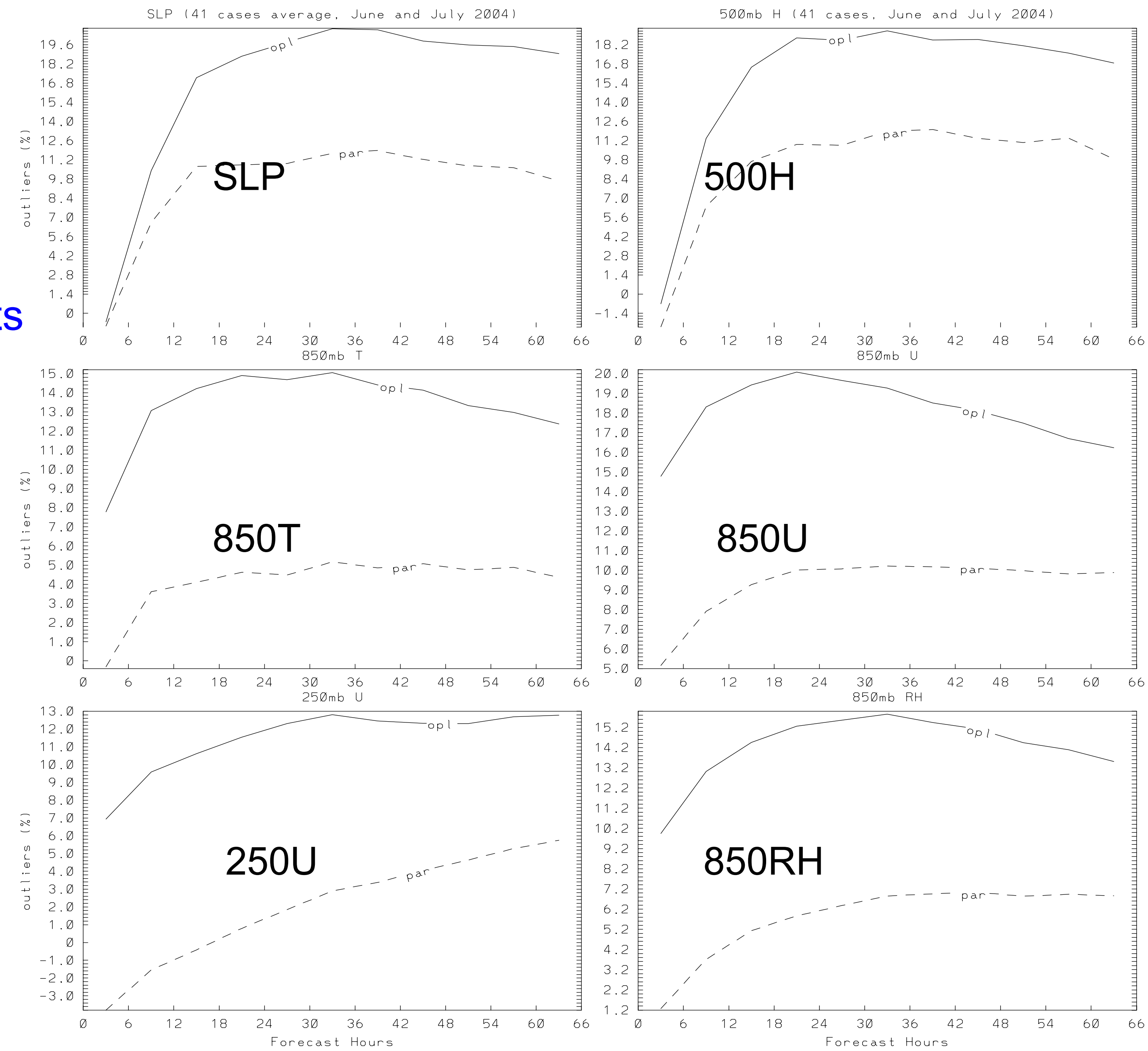




SREF Percentage of excessive outliers (41-case average)

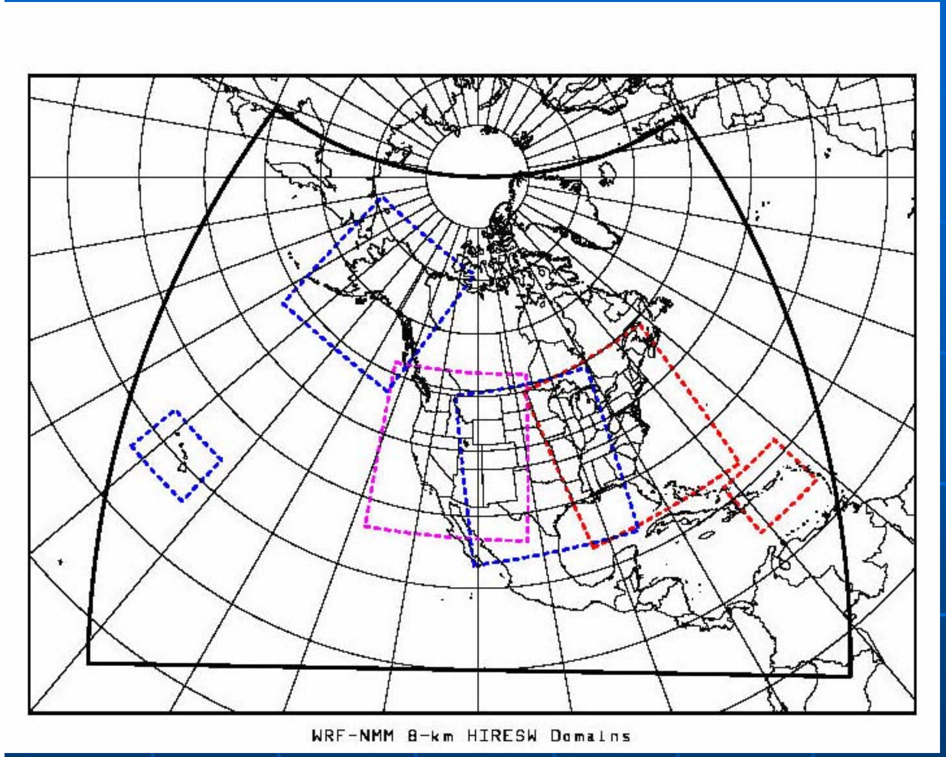
More physics diversity helps improve outlier stats

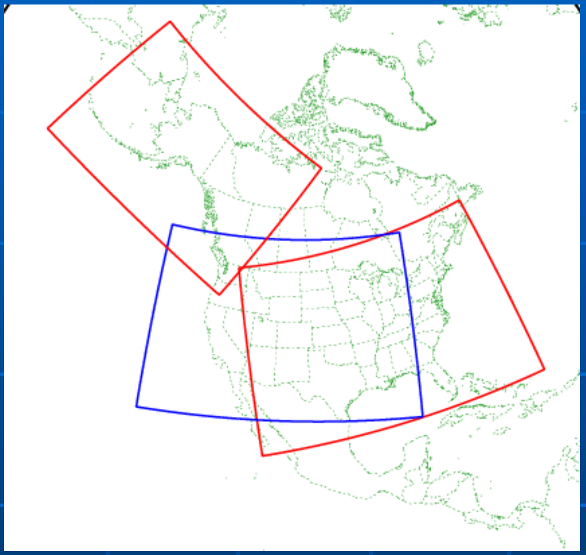
New: - - - - -
Old: ---------



Jun Du

HIRES Window 2007 Upgrade Domain Size Changes





Current Large & Small Domains

5.2 km for WRF-NMM

5.8 km for WRF-ARW

New Large Domains

4.0 km for WRF-NMM

5.1 km for WRF-ARW

Small domain size is unchanged

Jun Du

SYNERGY BETWEEN DA & ENSEMBLE FORECASTING

- **DA Objective** regarding initial conditions (Output)
  - Reduce growing errors
  - Eliminate non-growing errors
- **DA requirement** regarding forecasting (Input)
  - Plausible model trajectories (on attractor)
  - Associated forecast error covariance estimate
- **Ensemble forecasting objective** (Output)
  - Capture forecast error covariance
- **Ensemble forecasting requirement** (Input)
  - Analysis error variance

Analysis error variance

Forecast error covariance

SYNERGY BETWEEN DA & ENSEMBLE FORECASTING - 2

- For best DA/EF performance
  - Ensemble must capture expanding perturbations on slow manifold =>

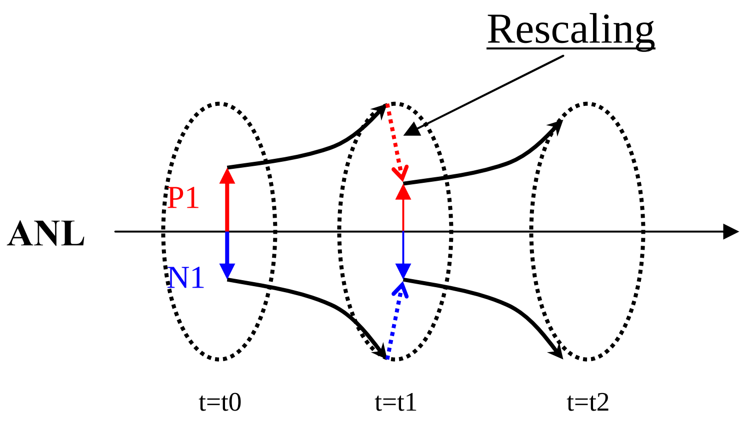
- Use breeding concept to generate ensemble
  - Introduce orthogonalization (Ensemble Transform)
    - Maximizes efficiency
  - Use simplex transformation
    - Centers perturbations around unperturbed analysis
    - Provides temporal consistency in perturbations (series of perturbed analyses)

  - Rescale perturbations
    - Sets initial variance according to analysis error estimate
      - Needed if ensemble membership is limited

- Couple with best available DA scheme
  - DA provides analysis error variance to EF
  - EF provides forecast error covariance to DA

- Ensemble-based DA methods (NOAA THORPEX work)
  - Must be based on same principles
    - 2-way interactions tuned simultaneously

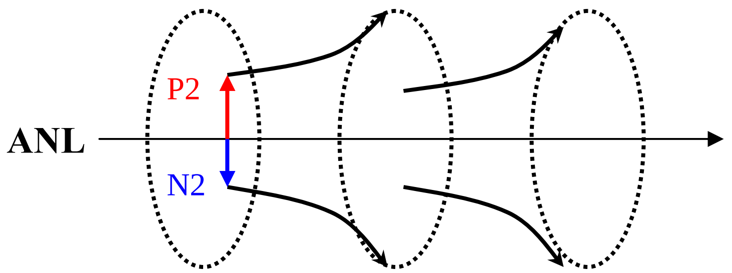
Bred Vector
(Former system)



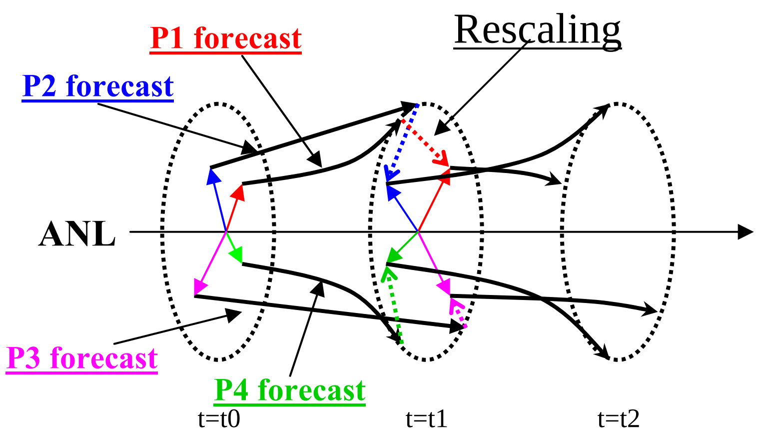
P#, N# are the pairs of positive and negative

P1 and P2 are quasi-independent vectors

Geographically dependent rescaling



Ensemble Transform Bred Vector
(Current system)



Ensemble Transform: P1, P2, P3, P4 are orthogonal vectors (ET)

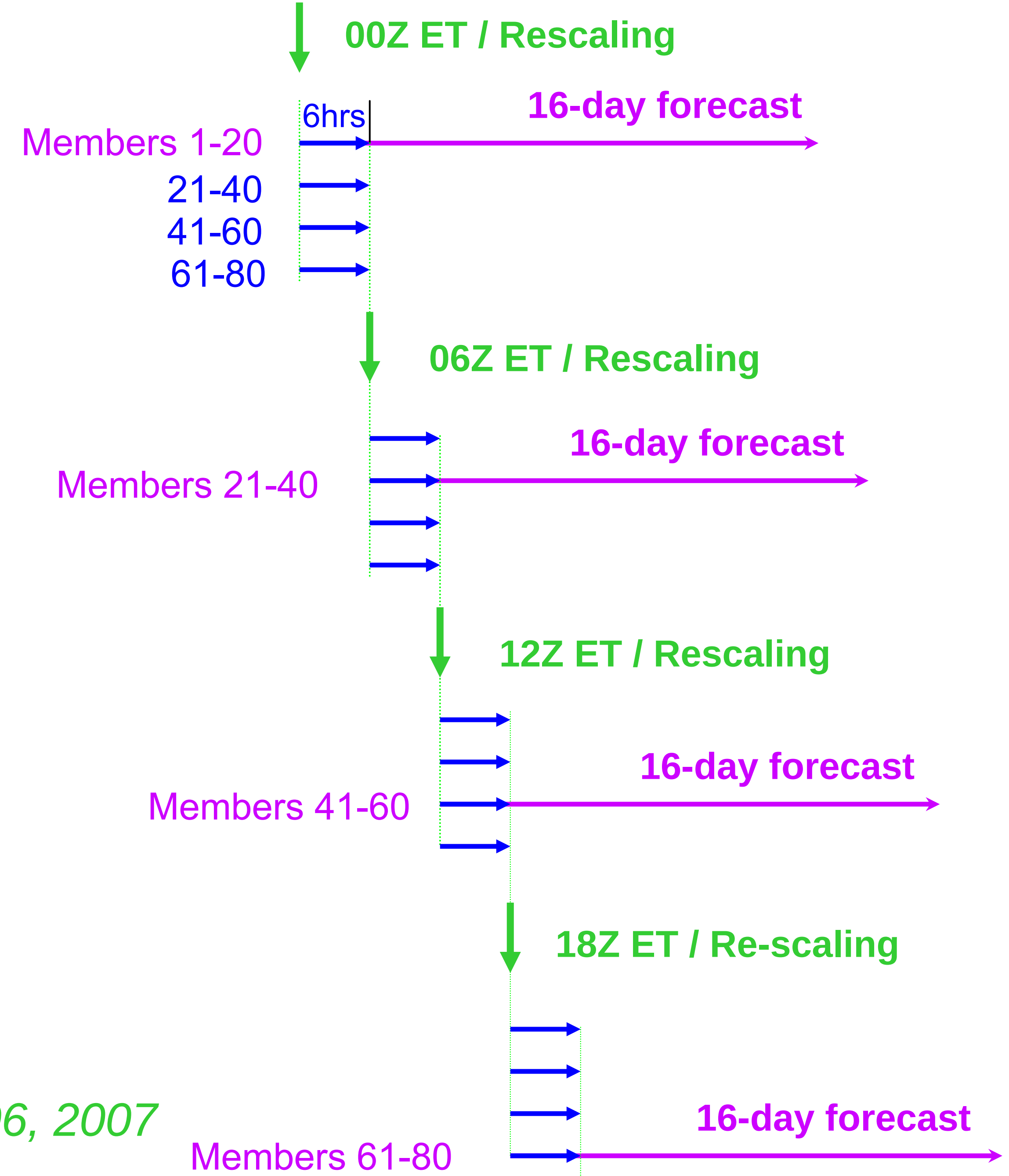
•No pairs any more

Simplex Transormation: Centralizes perturbations vectors (sum of all vectors are equal to zero)

Geographical Rescaling: Initial perturbation variance representative of analysis error variance

Wei et al. 2006, 2007

6-HOUR BREEDING CYCLE WITH ET / RESCALING



Wei et al. 2006, 2007

PROPERTIES OF BRED/ET/SIMPLEX/RESCALED PERTURBATIONS

- Flow dependent growth
  - Breeding
    - Support DA goal of reducing growing errors
- Orthogonal
  - ET
    - Efficiently spans growing subspace
- Centered on analysis
  - Simplex transformation
    - Best performance
- Temporally consistent
  - Simplex transformation
    - Important for wave, land surface etc ensembles where perts depend on the history
- Reflective of analysis uncertainty
  - Rescaling
    - Needed to improved forecast error covariance estimates

Wei et al. 2006, 2007

ESTIMATING ANALYSIS ERROR VARIANCE

- Current version of GSI does not provide explicit estimate
- How to produce case dependent analysis error estimates?
  - Courtier & Fisher 1995
    - Add-on feature to 3DVAR provides GSI-specific approximation
      - Statistically convert estimates for analysis variables
  - Inter-comparison of analyses from multiple centers
    - Default estimate (not GSI-specific)
- Use case-dependent 3D analysis error estimate
  - In total energy norm in
    - Ensemble Transformation as norm
    - Geographical rescaling as a mask

Wei et al.   2006, 2007

SYNERGY BETWEEN NUMEREICAL MODELING & ENSEMBLE FORECASTING

- **Numerical modeling community's objective** (Output)
  - Realism / fidelity of simulations
- **Numerical modeling community's requirement** (Input)
  - Reduction of forecast uncertainties
- **Ensemble forecasting objective** (Output)
  - Assessment of forecast uncertainties
- **Ensemble forecasting requirement** (Input)
  - Model related uncertainties

Assessment of model-related errors

Non-linear ensemble filtering of errors

SYNERGY BETWEEN NWP MODELING & ENSEMBLE - 2

- For best NWP/EF performance
  - Ensemble must capture all model related uncertainties at their origin
    - Otherwise uncertainty cannot be traced
      - From origin (particular model problem)
      - To destination (particular forecast aspect)

New NWP paradigm

- **Systematically assess uncertainty in every component** of NWP models
  - Prioritize work according to expected impact on ensemble

- **Reconstruct model components so they can simulate uncertainty**
  - Stochastic effect of truncation on resolved scales, in
    - Space (Subgrid-scale dynamics)
    - Time (Numerical accuracy)
    - Physics (Effect of parameterizations)
    - Etc

- ***Single model capable to (closely) reproduce nature*** with
  - Certain space/time configuration

Alternative

- Use of multiple forms/versions of models
  - Theoretically unappealing
    - Finite number of unconnected imperfect replicas of nature

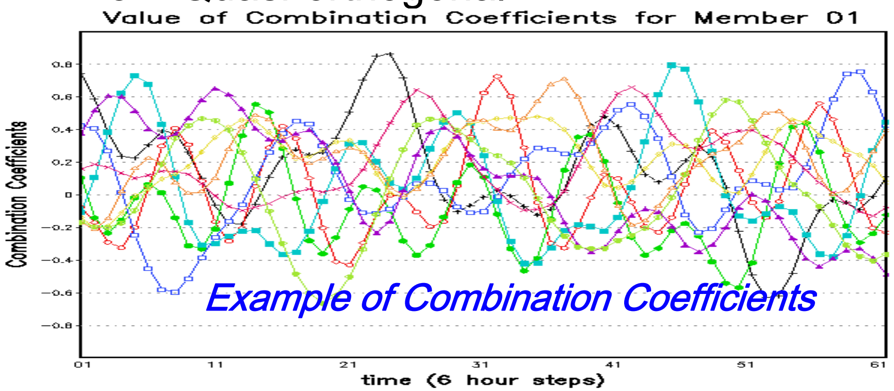
REPRESENTING MODEL RELATED UNCERTAINTY: A STOCHASTIC PERTURBATION (SP) SCHEME

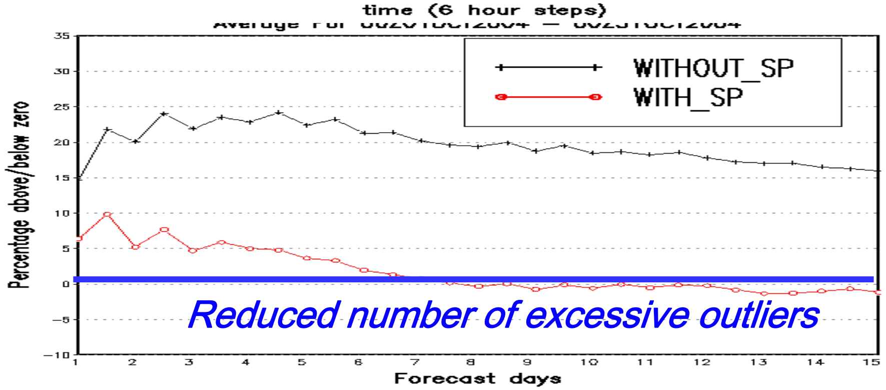
General Approach: Add a stochastic forcing term into the tendencies of the model eqs

Strategy: Generate the S terms from (random) linear combinations of the conventional perturbation tendencies.

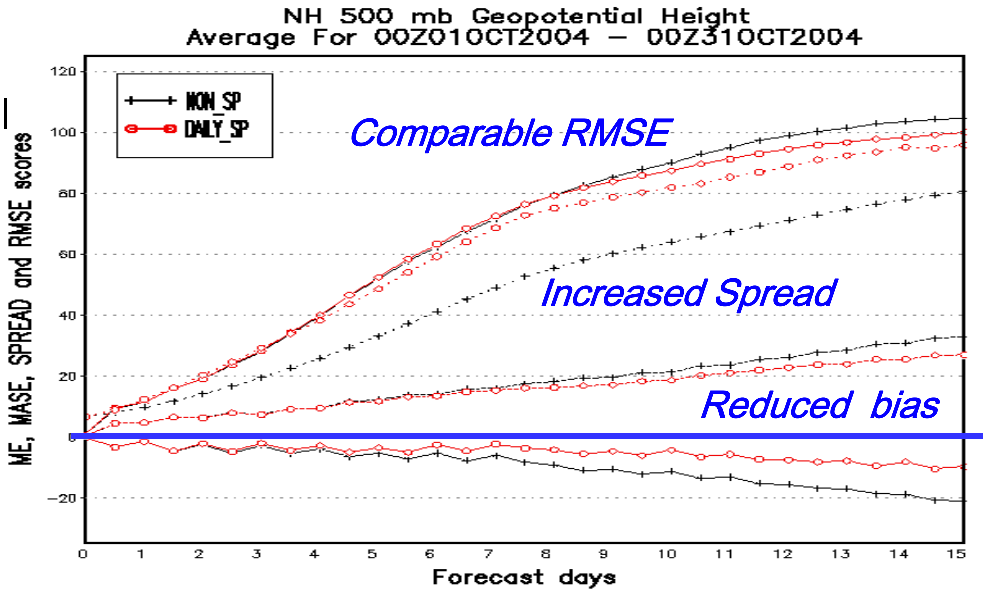
Desired Properties of Forcing

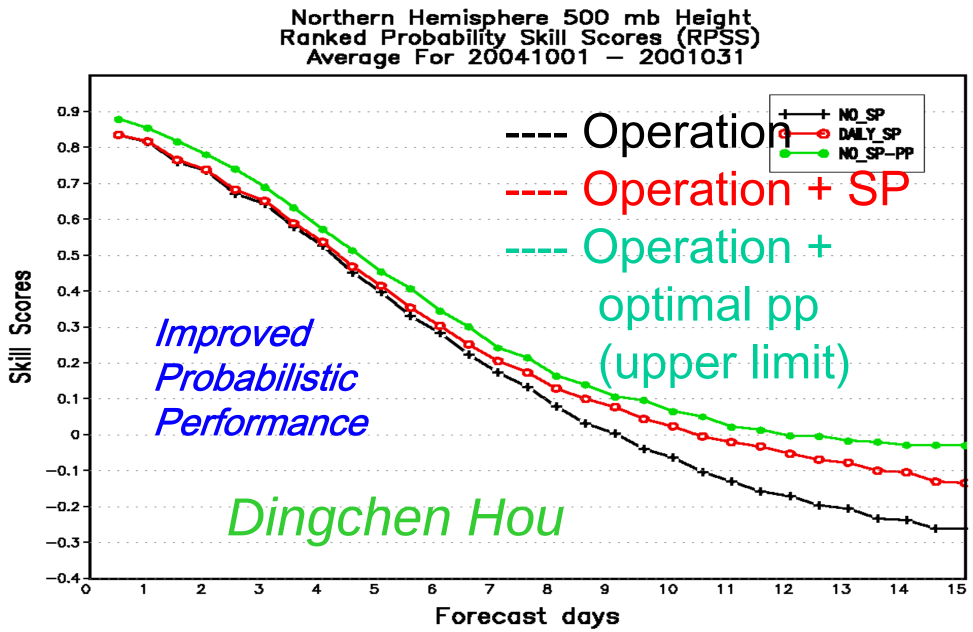
1. Applied to all variables
2. Approximately balanced
3. Smoothly varying in space and time
4. Flow dependent
5. Quasi-orthogonal





Goal: Represent effect of unresolved processes





SYNERGY BETWEEN STATISTICAL POSTPROCESSING & ENSEMBLE FORECASTING

- **Stat Post-processing Objective** (Output)
  - Calibrated pdf
- **Stat Post-processing requirement** (Input)
  - NWP forecasts
- **Ensemble forecasting objective** (Output)
  - Sample of trajectories
- **Ensemble forecasting requirement** (Input)
  - Statistical reliability

Statistical calibration

Ensemble trajectories

SYNERGY BETWEEN STATISTICAL POSTPROCESSING & ENSEMBLE FORECASTING - 2

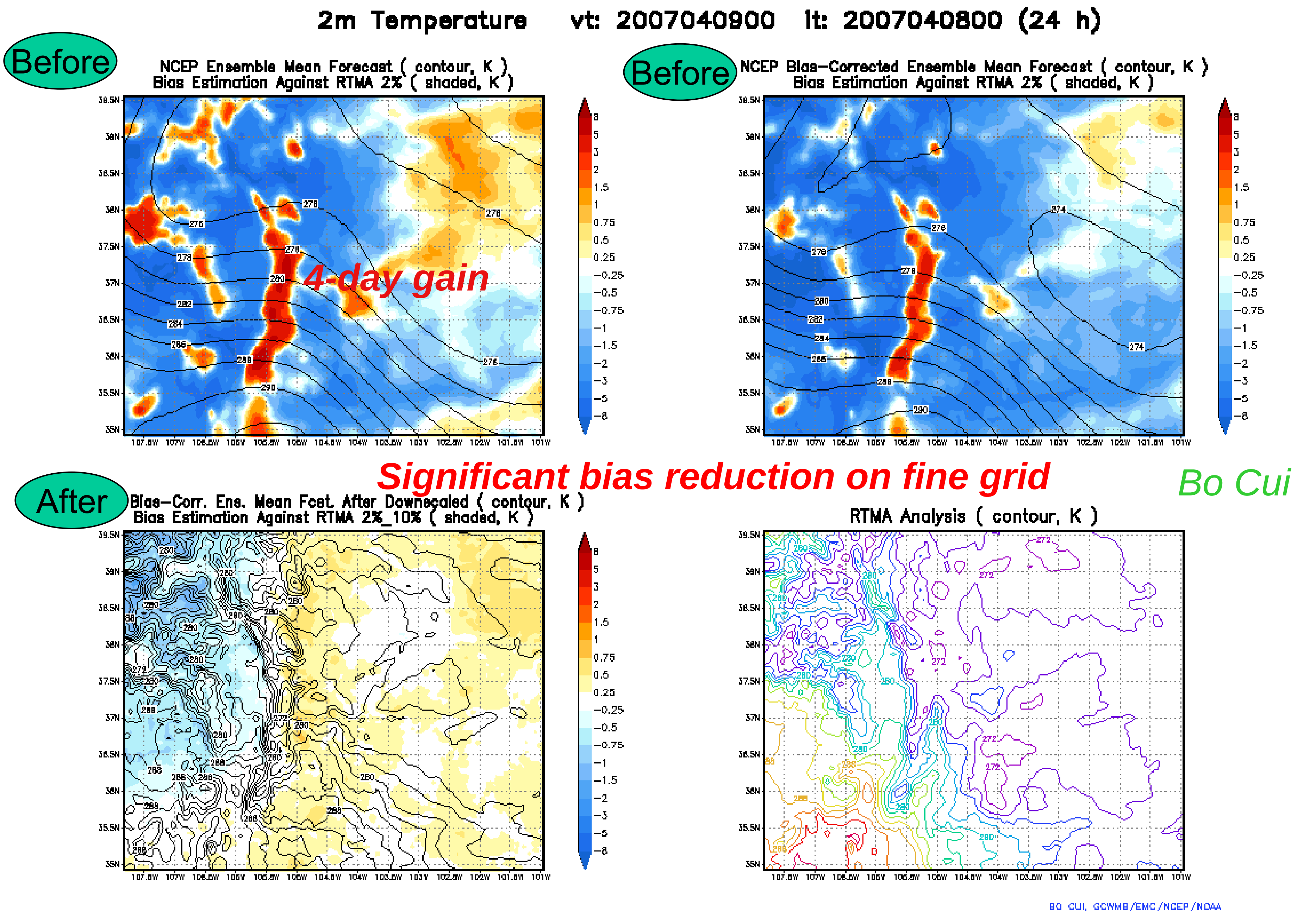
- For best EF/SPP performance
  - Fully couple EF & SPP

- Use **Bayesian estimator** to optimally combine
  - Prior (climate cdf)
  - Ensemble forecast information
    - Raw trajectories
    - Joint sample of ensemble and observed trajectories (error statistics)

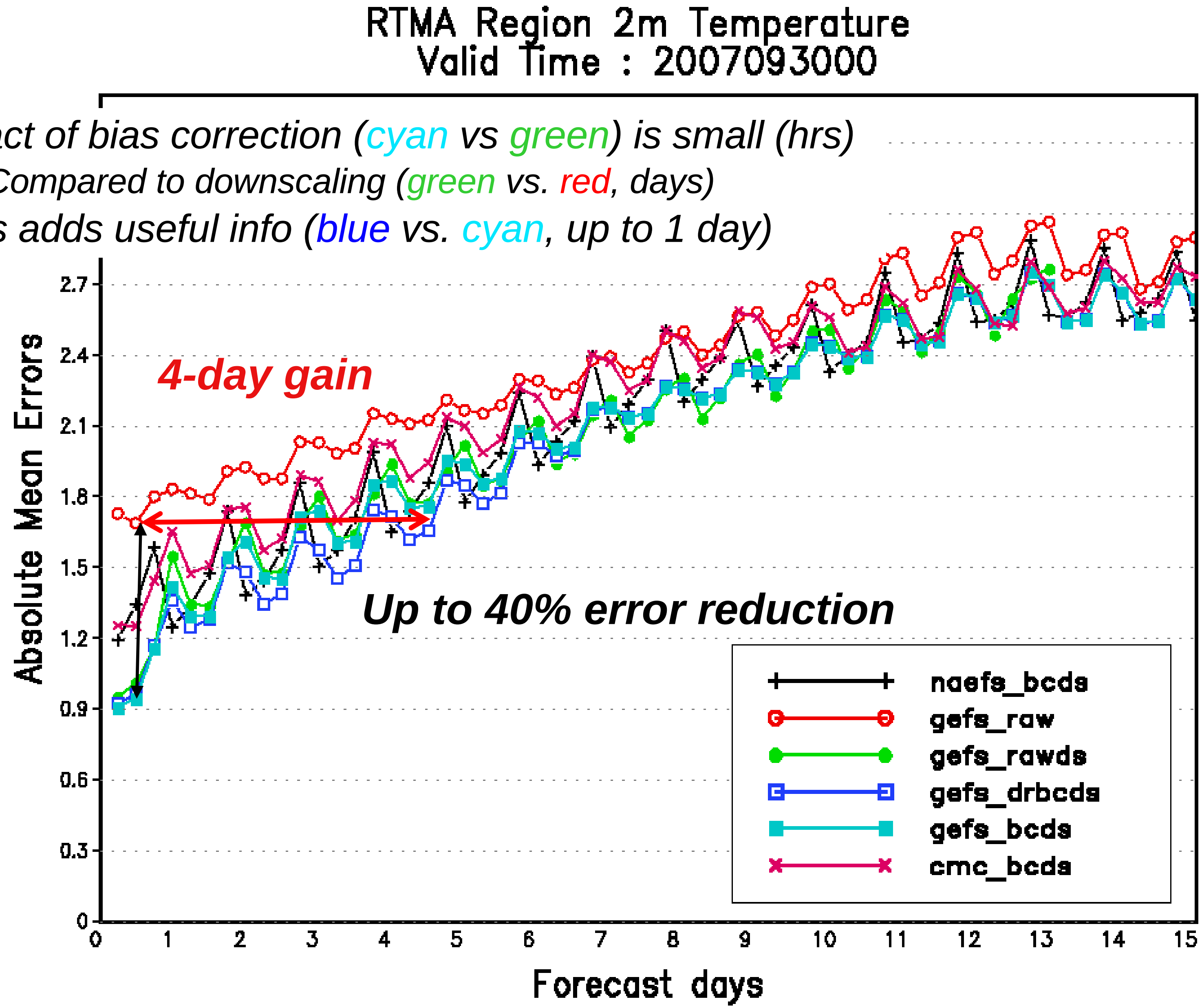
- Forecast **cdf bias correction** on model grid (30-120 km)
  - How important this step is (perfect ensemble assumption good)?
  - How large sample is needed?

- **Downscaling** to fine grid (~5 km)
  - Based on relationship between coarse and fine resolution analysis fields
    - ***No hind-casts needed!***

Fcst: 24hr Ensemble Mean & Bias Before/After Downscaling 10%



- *Impact of bias correction (cyan vs green) is small (hrs)*
  - *Compared to downscaling (green vs. red, days)*
- *Hires adds useful info (blue vs. cyan, up to 1 day)*

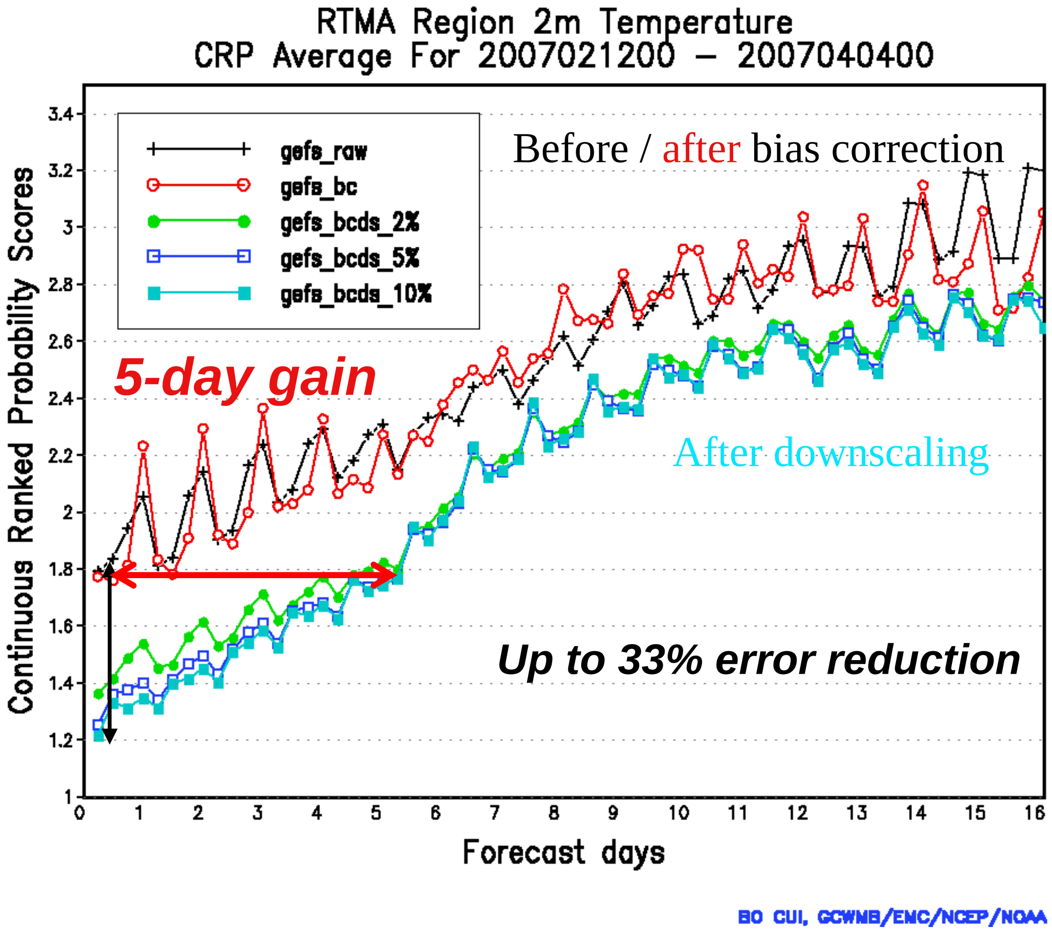


Bo Cui

dr=dual resolution, bc=bias correction, ds=downscaling, raw=direct output

2m Temperature: Continuous Ranked Probability Score (CRPS)

Average for 20070212 to 20070404



Bo Cui

Preliminary results:

- ***Major improvement in skill of fine-scale forecasts:*** Downscaled & bias-corrected ensemble forecasts have significant improvements compared with raw & calibrated forecast for all lead time (downscaled 5+day forecast as skillful as raw 6-hr forecast)

- 10% weighting is better than 2% and 5% weighting in short range. ~30% improvement with 10% weighting for d0-d4. The 2%, 5% and 10% weighting curves are close for long range. Will add more high weights for comparison.

Limitation:

- **small samples**
- **more samples needed**

SYNERGY BETWEEN PRODUCT GENERATION & ENSEMBLE FORECASTING

- **Product generation Objective** (Output)
  - Any user product
- **Product generation requirement** (Input)
  - Single value estimate of atmospheric condition
- **Ensemble forecasting objective** (Output)
  - “Forcing” trajectories
- **Ensemble forecasting requirement** (Input)
  - User relevant information

User relevant processing

Ensemble trajectories

SYNERGY BETWEEN PRODUCT GENERATION & ENSEMBLE FORECASTING - 2

- For best EF/PG performance
  - Fully couple EF & PG

- **Use each ensemble trajectory of weather** to
  - Simulate corresponding user relevant events
    - Powerful quantitative assessment of expected effect of weather on user operations

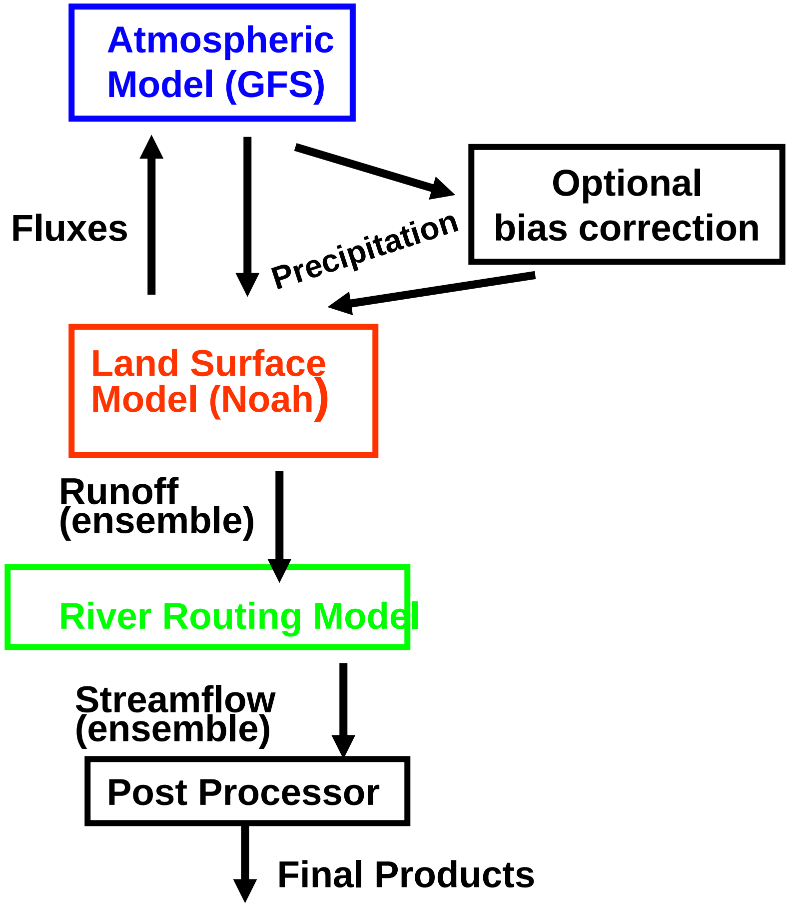
  - Decision Support System must be based on quantitative analysis of results

- Alternatives
  - Various types of qualitative analyses can also be useful in
    - Complex situations that are hard to quantitatively assess
  - Related to **summary statistics from ensemble** can be used

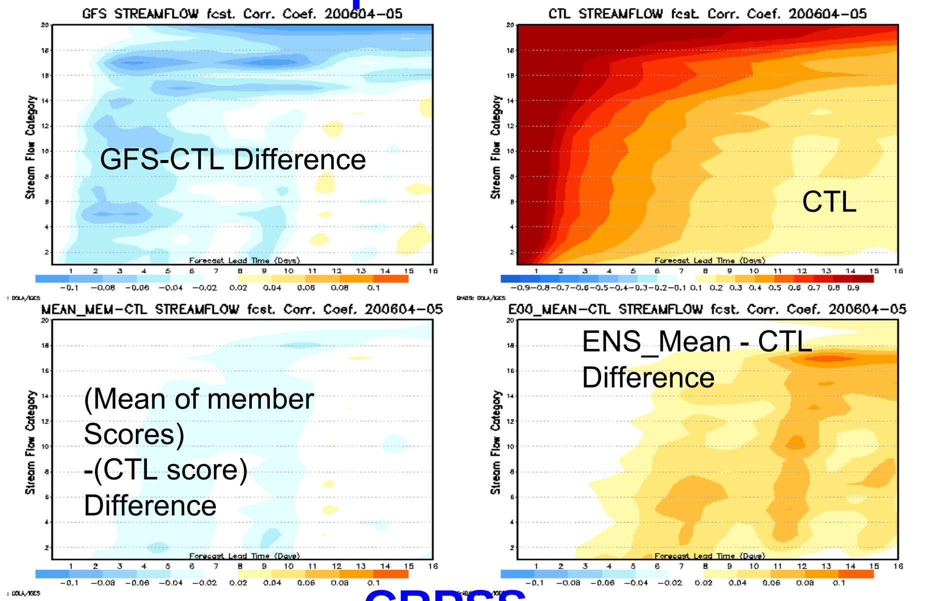
Experimental Medium-range Ensemble Streamflow Forecasts Based on Coupled GFS-Noah Ensemble Runoff Forecast

Dingchen Hou, Kenneth Mitchell, Zoltan Toth, Dag Lohmann and Helin Wei

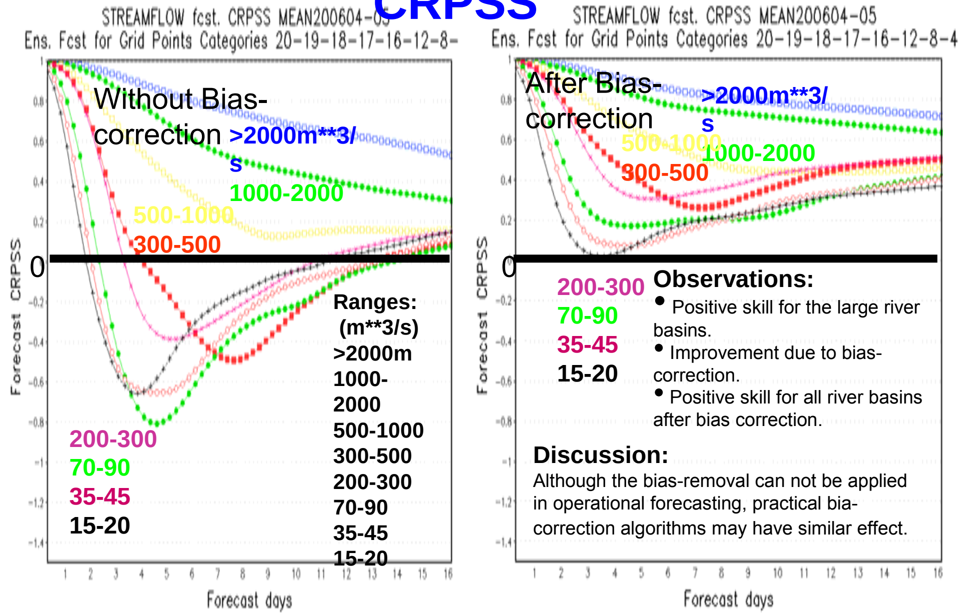
Ensemble Streamflow Forecast
Two Possible Approaches
One way and two way coupling



Temporal Correlation



CRPSS



Potomac River, Washington DC
A Medium Sized Basin, May 4th

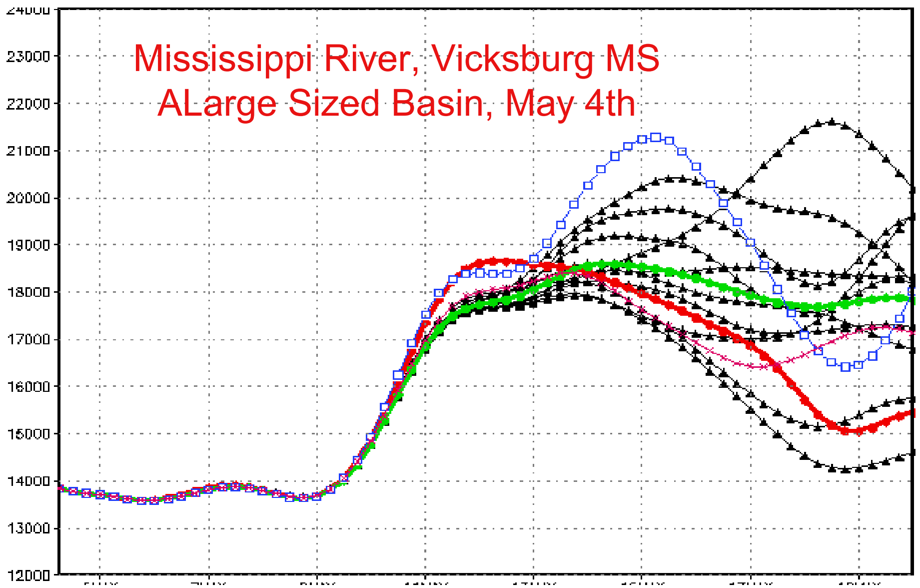
----- GEFS members
----- GEFS ens. mean
----- GEFS control
----- GFS high resolution
----- NLDAS

0 2 4 6 8 10 12 14 16
Lead Time (days)

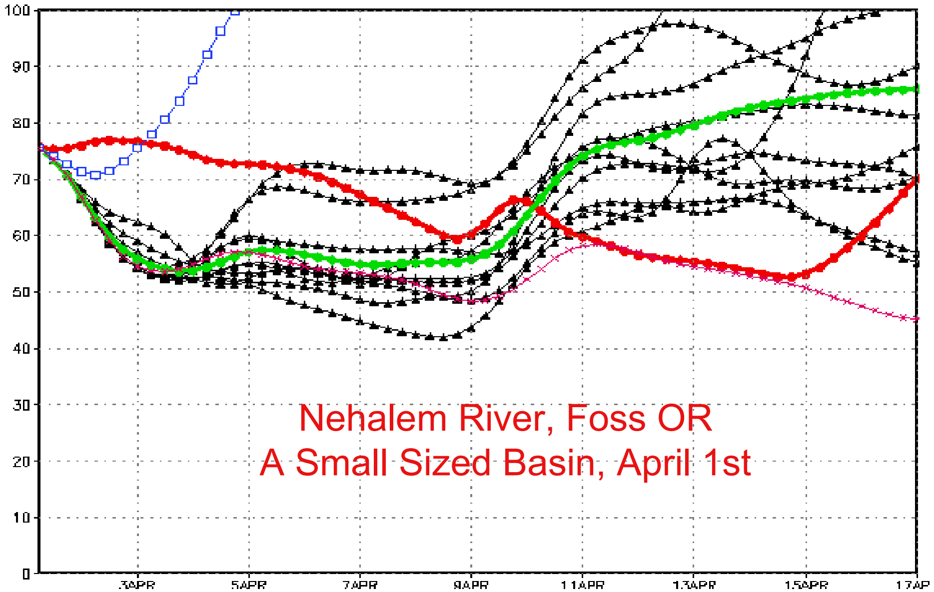
Summary of Results

- Distributed river routing ensemble system (coupled GEFS, Noah and the river routing model used) works well with the variability in the ensemble streamflow forecasts being of the same order of magnitude as the error in the mean of the ensemble
- For large basins, the ensemble streamflow forecasts appear to capture well the variations in the NLDAS analysis of streamflow
- For medium- and small-sized basins, a serious under-dispersion is present in the spread of the ensemble streamflow forecasts. This is likely due to a lack of sufficient variability in the precipitation forcing on the scale of the chosen river basin

Dingchen Hou



0 2 4 6 8 10 12 14 16
Lead Time (days)



0 2 4 6 8 10 12 14 16
Lead Time (days)

OUTLINE / SUMMARY

- OBJECTIVE OF ENSEMBLE FORECASTING
  - GENERATE FINITE SAMPLE OF PLAUSIBLE SOLUTIONS

- NCEP ENSEMBLE FORECAST SYSTEMS
  - SEASONAL
  - GLOBAL
  - REGIONAL
  - HIGH IMPACT

- COMPONENTS OF ENSEMBLE FORECASTING
  - INITIAL PERTURBATIONS
    - Interface with DA
  - MODEL-RELATED PERTURBATIONS
    - Interface with numerical modeling
  - STATISTICAL CORRECTIONS
    - Bias correction – Correcting lead time dependent systematic errors
    - Downscaling – No forecasting involved
  - APPLICATIONS
    - Decision Support Systems

BACKGROUND

NAEFS BENEFITS

- **Improves probabilistic forecast performance**
  - Earlier warnings for severe weather
    - Lower detection threshold due to more ensemble members
    - Uncertainty better captured via analysis/model/ensemble diversity (assumed)
- **Provides Seamless suite of forecasts** across
  - International boundaries
    - Canada, Mexico, USA
  - Different time ranges (1-14 days)
- **Saves development costs** by
  - Sharing scientific algorithms, codes, scripts
    - Accelerated implementation schedule
    - Low-cost diversity via multi-center analysis/model/ensemble methods
  - Exchanging complementary application tools
    - MSC focus on end users (public)
    - NWS focus on intermediate user (forecaster)
- **Saves production costs** by
  - Leveraging computational resources
    - Each center needs to run only fraction of total ensemble members
  - Providing back-up for operations in case of emergencies
    - Use nearly identical operational procedures at both centers to provide basic products
    - Offers as default basic products based on unaffected center's ensemble

THORPEX
A World Weather Research Programme

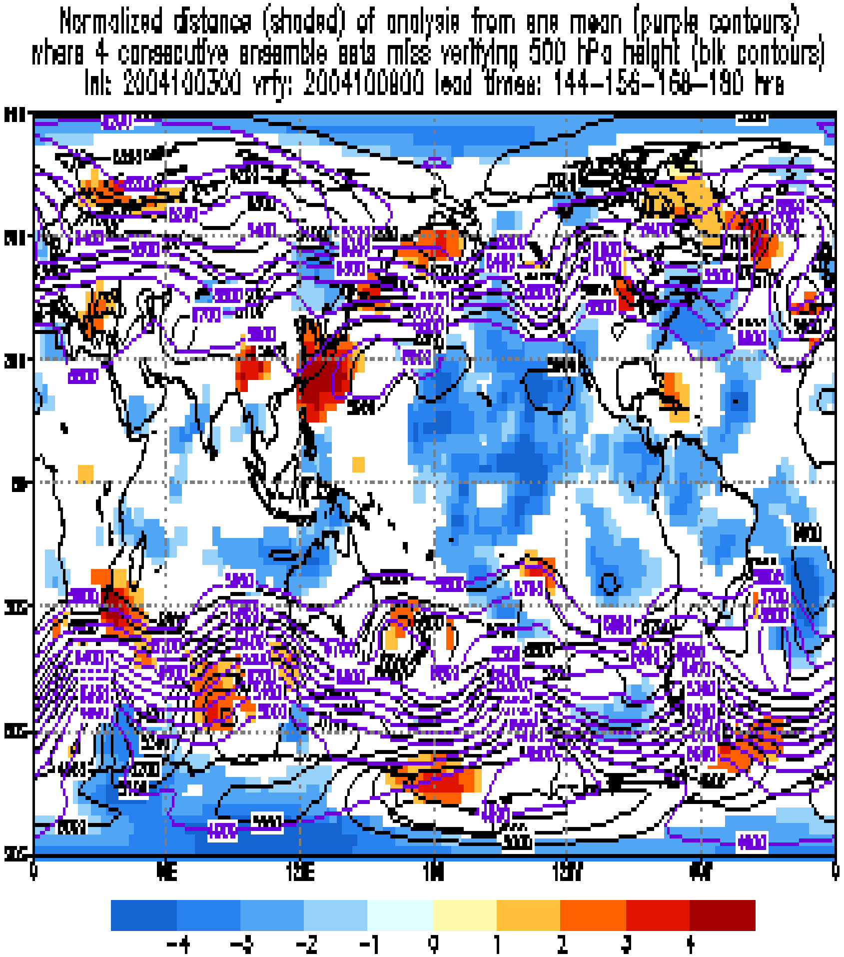
NAEFS HISTORY & MILESTONES

- February 2003, Long Beach, CA
  - NOAA / MSC high level agreement about joint ensemble research/development work (J. Hayes, L. Uccellini, D. Rogers, M. Beland, P. Dubreuil, J. Abraham)
- May 2003, Montreal (MSC)
  - 1st NAEFS Workshop, ***planning started***
- November 2003, MSC & NWS
  - 1st draft of NAEFS Research, Development & Implementation Plan complete
- May 2004, Camp Springs, MD (NCEP)
  - Executive Review
- September 2004, MSC & NWS
  - ***Initial Operational Capability*** implemented at MSC & NWS
- November 2004, Camp Springs
  - Inauguration ceremony & 2nd NAEFS Workshop
    - Leaders of NMS of Canada, Mexico, USA signed memorandum
    - 50 scientists from 5 countries & 8 agencies
- May 2006, Montreal
  - 3rd NAEFS Workshop
- May-Oct 2006, MSC & NWS
  - ***1st Operational Implementation***
    - Bias correction
    - Climate anomaly forecasts
- 2007-2008, MSC, NWS
  - Follow-up implementations
    - Improved and expanded product suite

Outliers: H500, day 6 forecast, 20041002

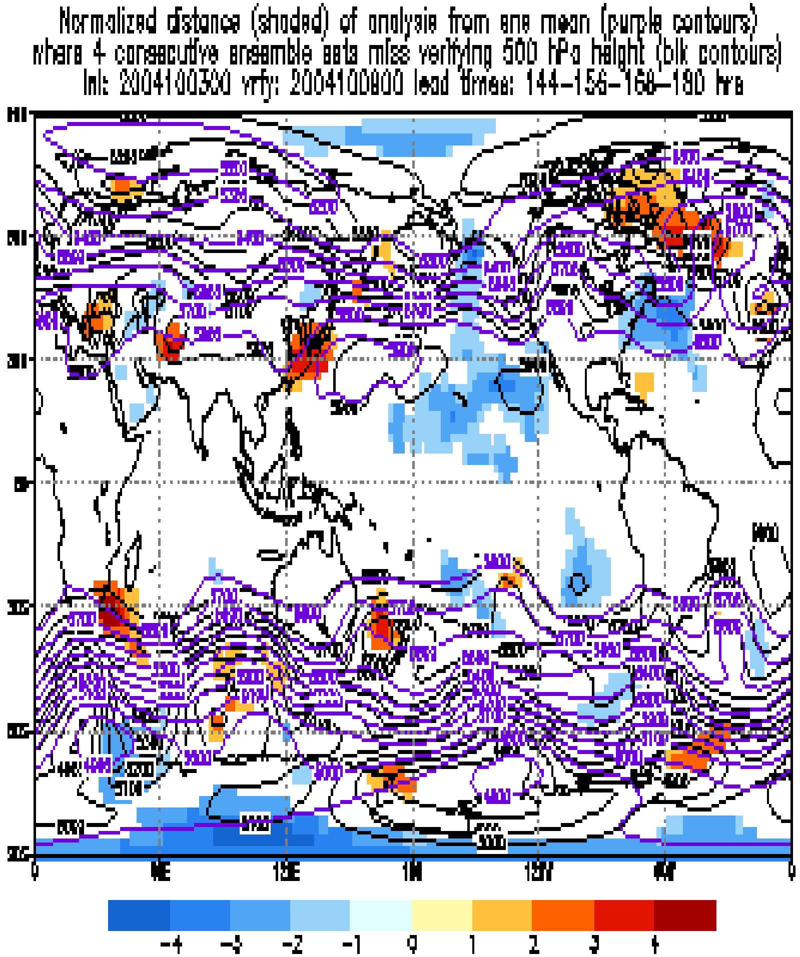
Without SP

large number of outliers with negative and positive forecast bias

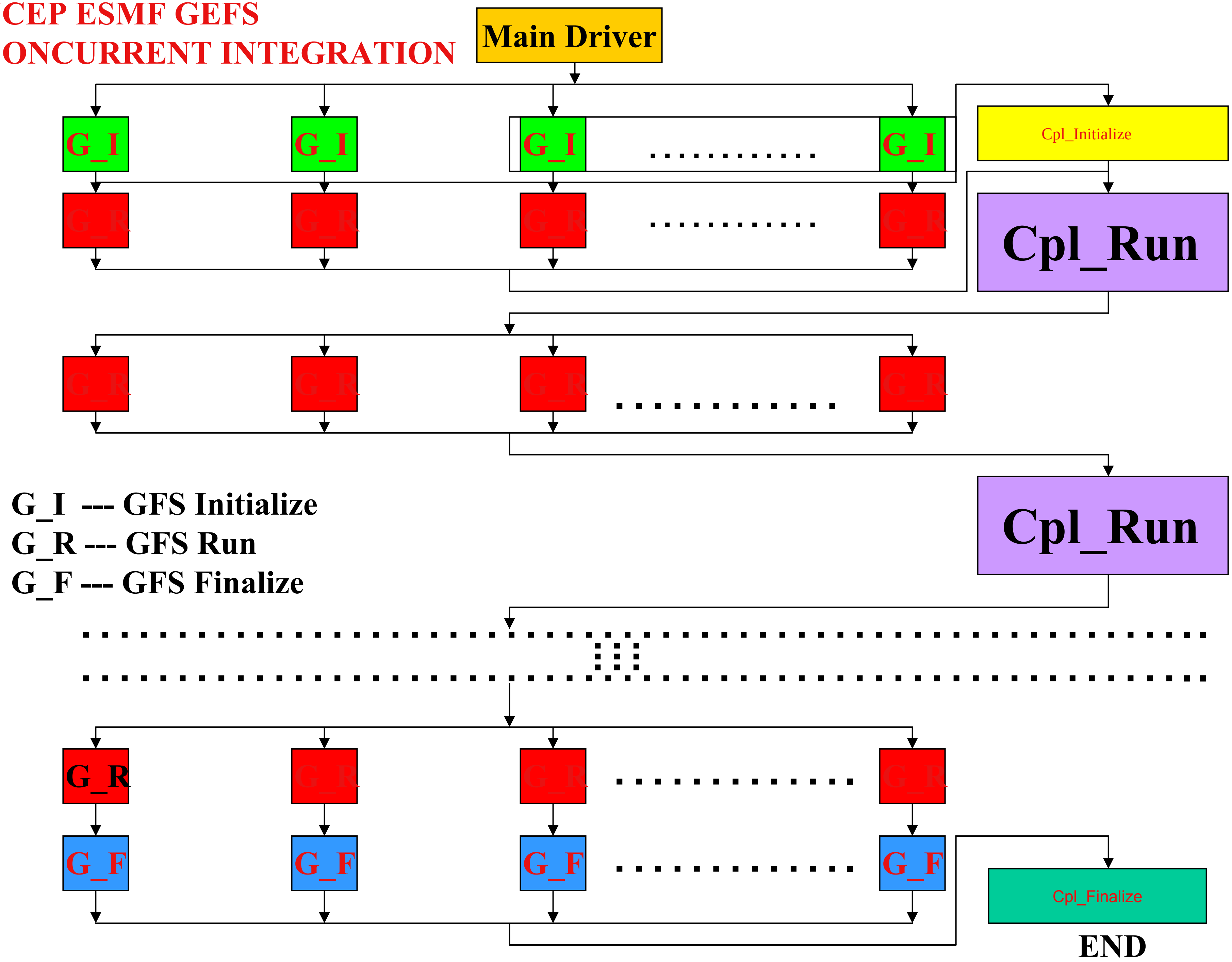


With SP

the number of outliers is significantly reduced



NCEP ESMF GEFS CONCURRENT INTEGRATION



Experimental Medium-range Ensemble Streamflow Forecasts Based on Coupled GFS-Noah Ensemble Runoff Forecast

Dingchen Hou, Kenneth Mitchell, Zoltan Toth, Dag Lohmann and Helin Wei

Background:

Land Surface component of NCEP coupled weather/climate prediction models (Mitchell et al, 2005) facilitates streamflow forecasts from theses coupled systems.

River routing experiment in analysis mode of the NLDAS project (Lohmann et al, 2004) revealed potential extension to river flow forecasts in coupled prediction models.

Existence of uncertainty in initial conditions, model structure and land surface forcing needs to be considered with an ensemble approach.

Purpose:

Demonstrate feasibility of gridded medium-range river flow forecast in operational NCEP Global Ensemble Forecast System (GEFS).

Develop strategy to represent uncertainties.

Extent the concept to the seasonal range by utilizing ensemble coupled CFS/Noah prediction of runoff in the future.

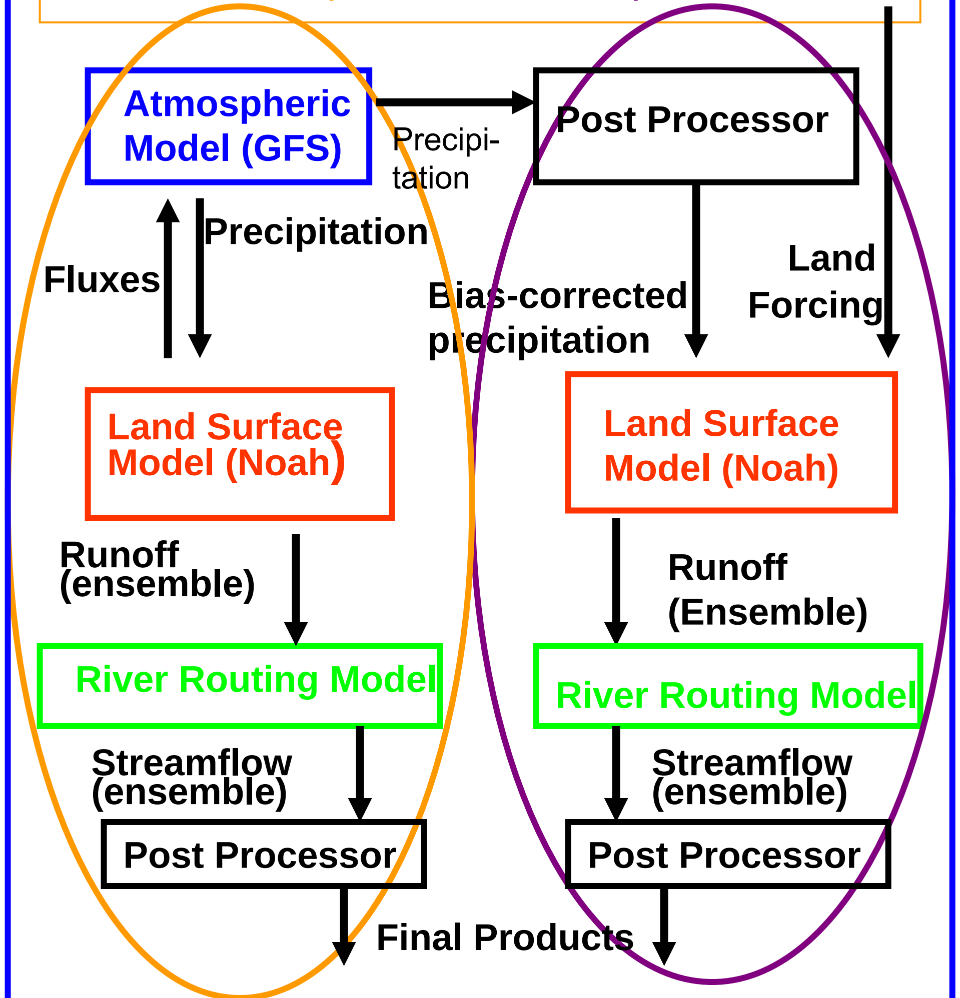
General Strategy:

NLDAS stream flow analysis used as initial condition and verification;

Extension to global domain in mind with domestic and international users;

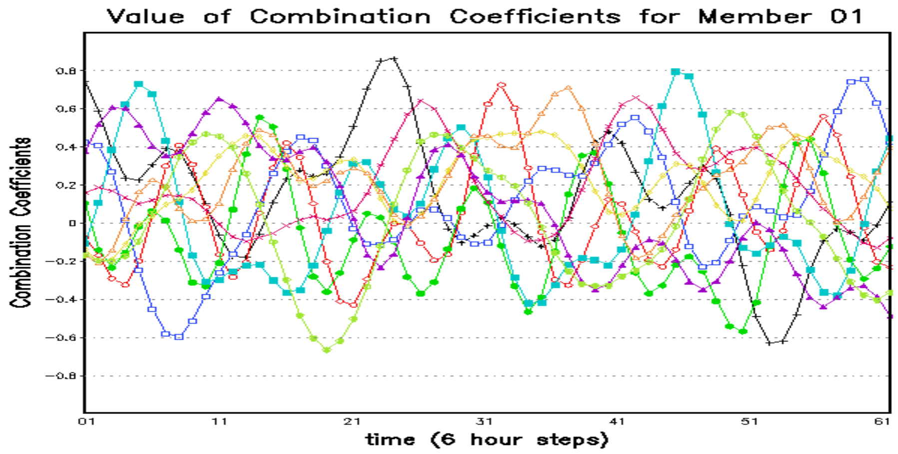
Hind cast data set to be generated for post pressing.

Ensemble Streamflow Forecast
Two Possible Approaches
Coupled and Uncoupled



Representing Model Related Uncertainty
A Proposed Stochastic Perturbation Scheme

General Approach: Adding a stochastic forcing term in to the tendencies of the model equations.
Assumption: The perturbations (difference between ensemble members and the control) in the conventional tendencies provide a sample of realizations of the additional stochastic forcing S.



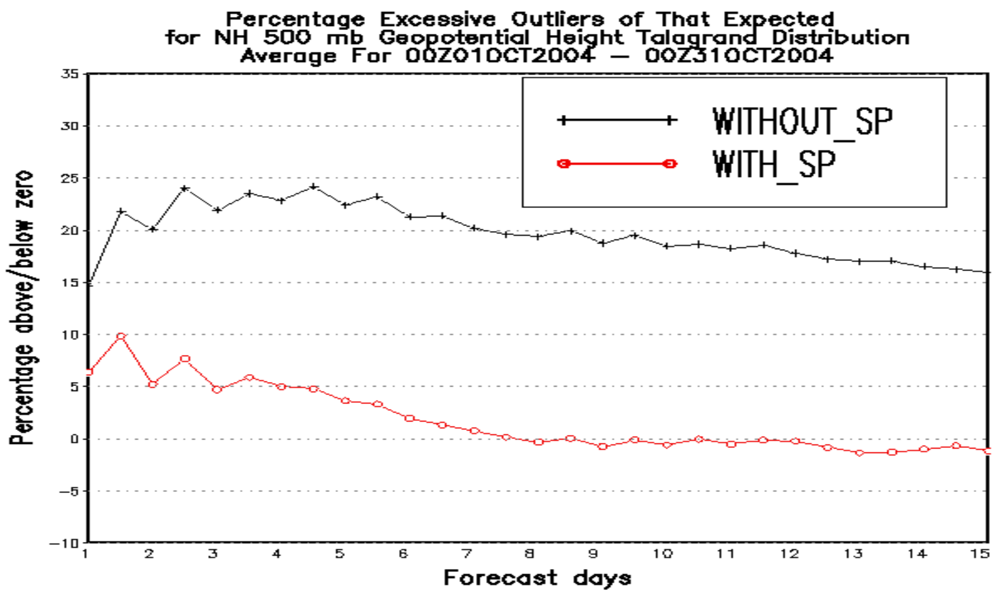
Strategy: Generate the S terms from (random) linear combinations of the conventional perturbation tendencies.

Desired Properties

1. Forcing applied to all variables
2. Approximately balanced
3. Smooth variation in space and time
4. Flow dependent
5. Quasi-orthogonal

Expected Results

Increased spread
Reduced systematic error
Improved probabilistic forecast

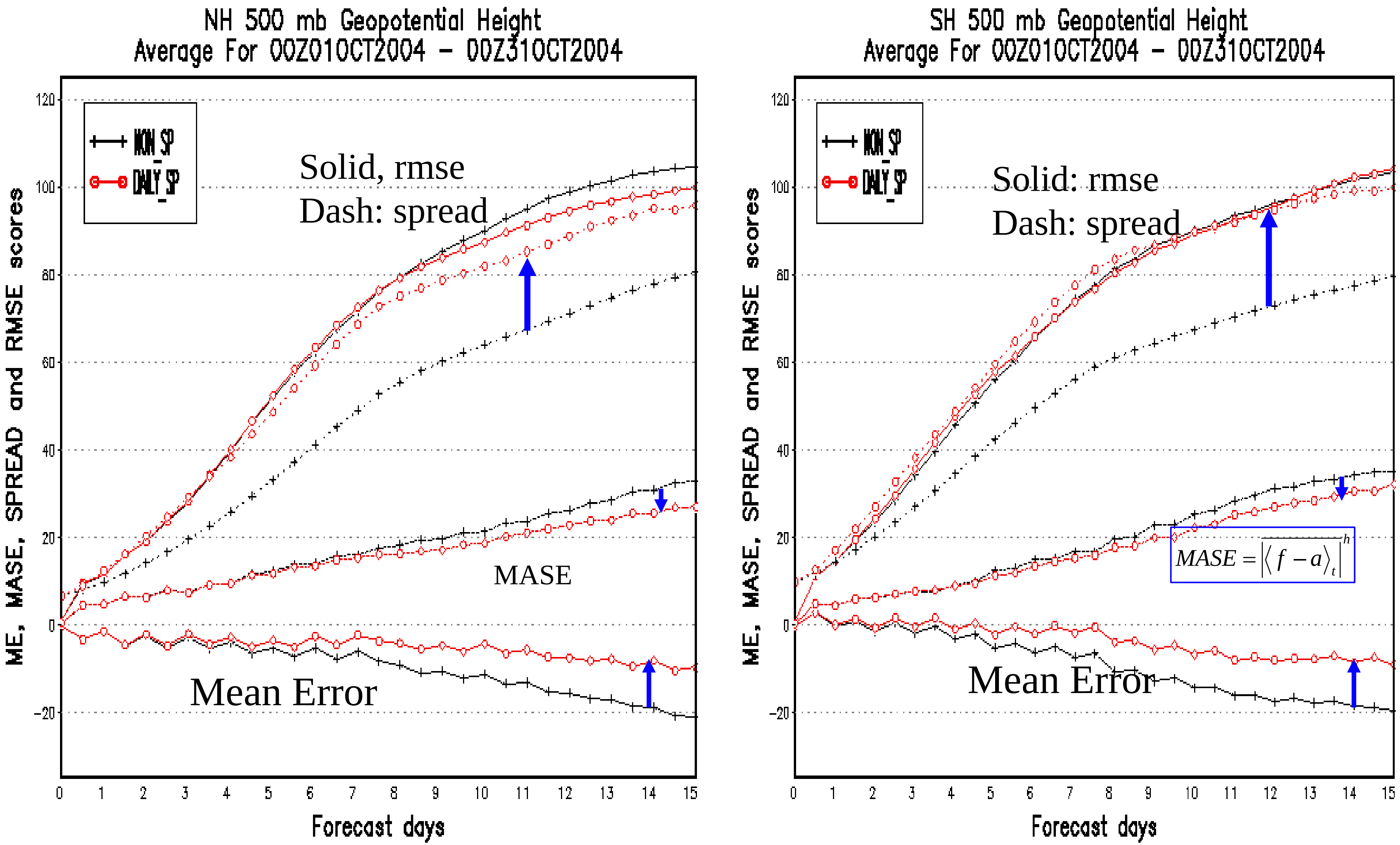


Statistics: Ensemble Spread and Error of Ensemble Mean

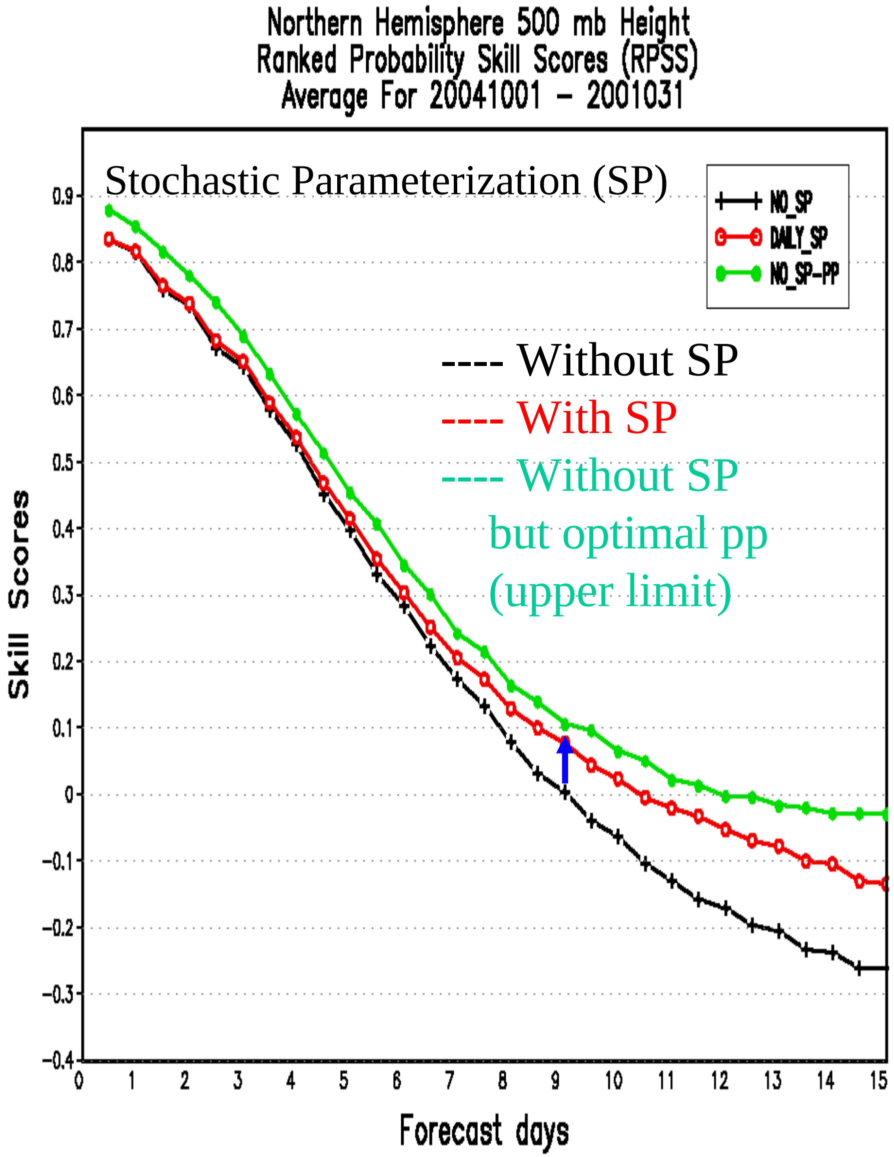
Increased Spread, Reduced Mean Error (ME)

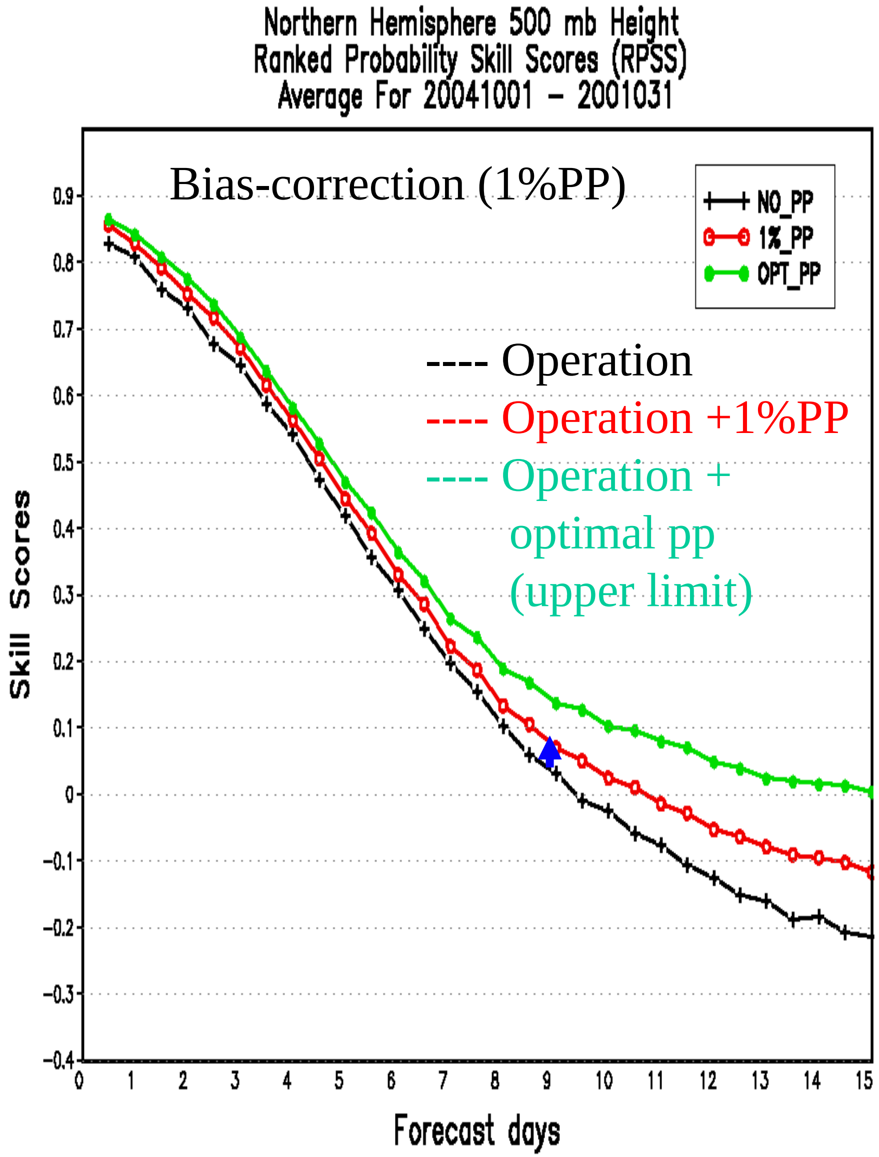
Reduced Mean Absolute Systematic Error (MASE)

----- Without SP ------- With SP



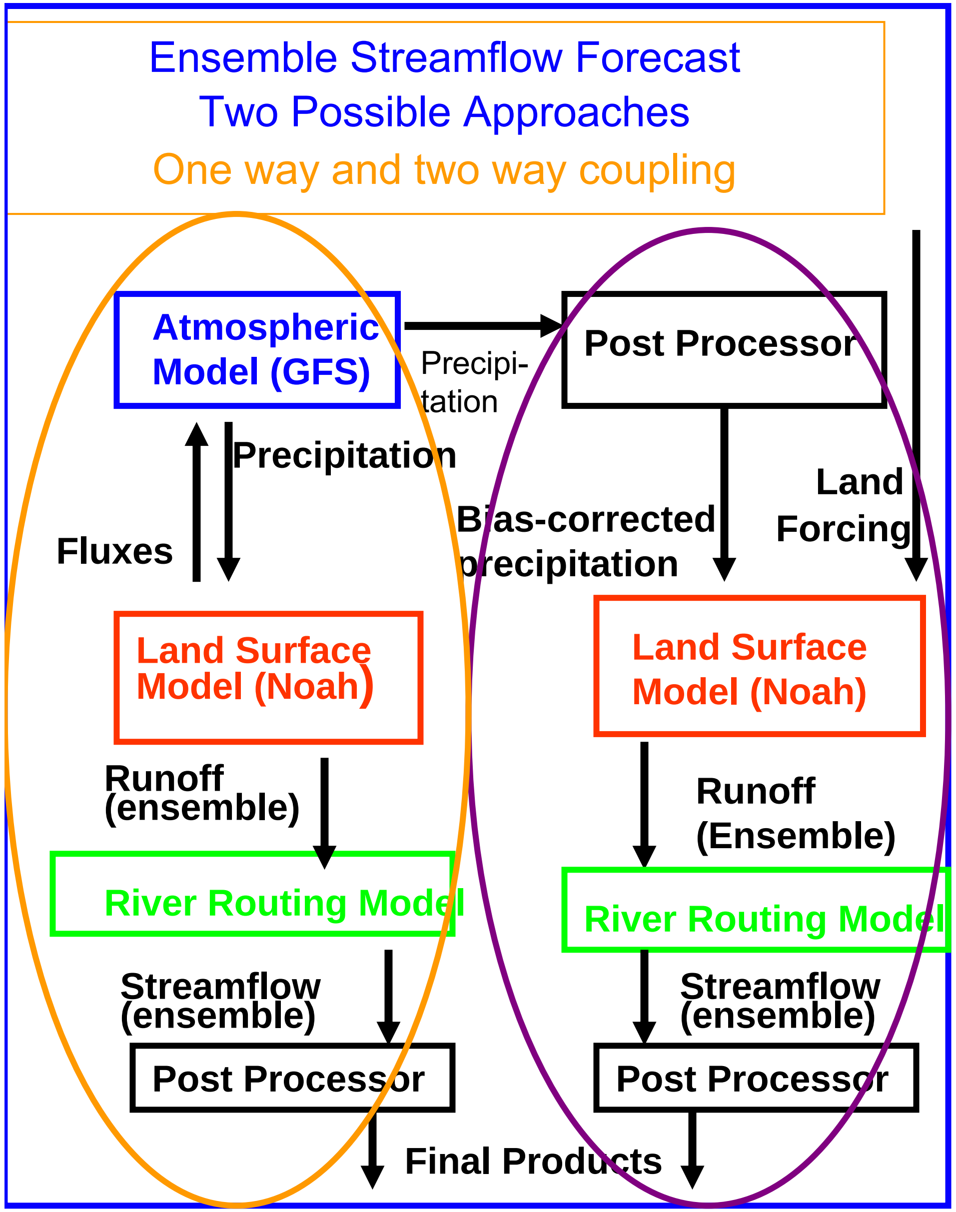
Comparison with Post-Processing (PP)
RPSS: Improved in both cases (SP and PP)
SP is more effective in week 2 forecast



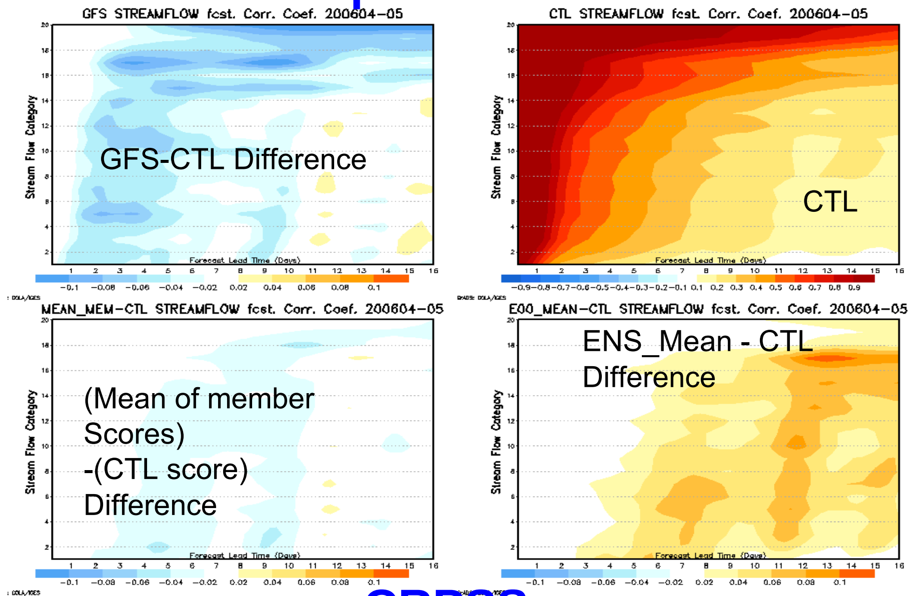


Experimental Medium-range Ensemble Streamflow Forecasts Based on Coupled GFS-Noah Ensemble Runoff Forecast

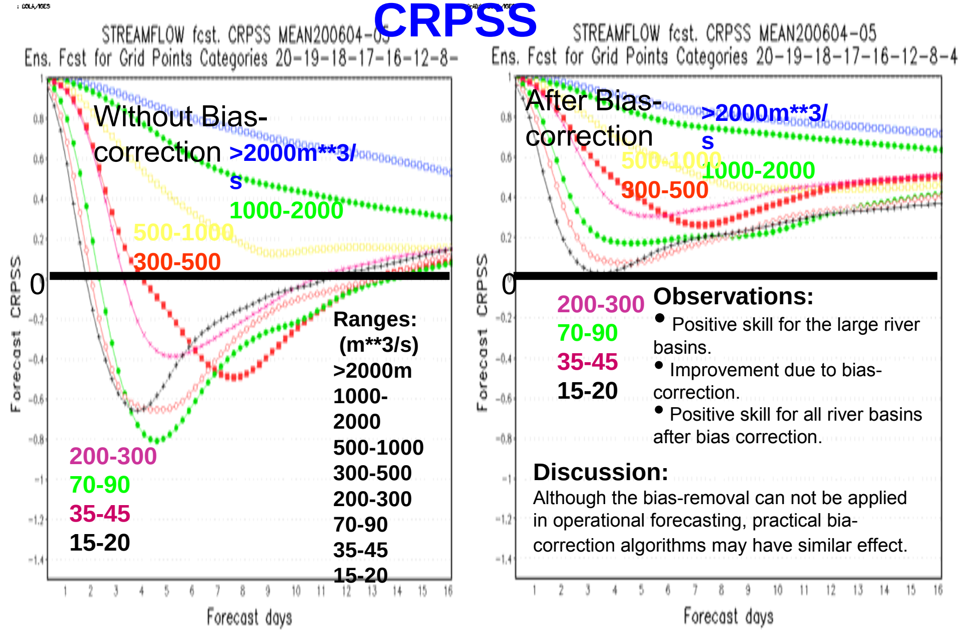
Dingchen Hou, Kenneth Mitchell, Zoltan Toth, Dag Lohmann and Helin Wei



Temporal Correlation



CRPSS



HOW TO REPRESENT INITIAL VALUE RELATED UNCERTRAINTY?

- **Proposed solution:** Dynamical sampling in growing sub-space – ET / ETKF

- Link with DA (GSI – ET)
  - Need collaboration between DA and ensemble teams.
  - Take error variance from GSI to specify ensemble perturbations
  - Feed back information from ensemble into background error covariance.
  - ET provides series of perturbed analyses consistent in time
    - Important for wave, land surface ensembles etc where perts depend on the history.

- Ensemble-based DA – ETKF
  - Same ensemble principles, except 2-way interactions tuned simultaneously.

Unified EFS and DA

- *EFS and DA systems must be consistent for best performance of both.*
- SSI/GSI currently *provides best estimate of analysis, GSI will be used to derive analysis uncertainties (error variance) for EFS.*
- *EFS produces flow dependent forecast (background) error covariance to be tested in GSI later.*

A Hybrid DA-EFS System

$$\text{GSI} \xrightarrow{\text{Best analysis error variances } (diag(\mathbf{P}^a))} \text{EFS}$$

$$\text{GSI} \xleftarrow[\text{Accurate forecast error covariance } \mathbf{P}^f \text{ or } \mathbf{B}]{} \text{EFS}$$

SAMPLING INITIAL CONDITION ERRORS

CAN SAMPLE ONLY WHAT'S KNOWN – FIRST NEED TO

ESTIMATE INITIAL ERROR DISTRIBUTION

THEORETICAL UNDERSTANDING – THE MORE ADVANCED A SCHEME IS (e. g., 4DVAR, Ensemble Kalman Filter)

- The lower the overall error level is
- The more the error is concentrated in subspace of Lyapunov/Bred vectors

PRACTICAL APPROACHES –

ONLY SOLUTION IS MONTE CARLO (ENSEMBLE) SIMULATION

- ***Statistical approach*** (dynamically growing errors neglected)
  - Selected estimated statistical properties of analysis error reproduced
    - Baumhefner et al – Spatial distribution; wavenumber spectra
    - ECMWF – Implicite constraint with use of Total Energy norm
- ***Dynamical approach*** – Breeding cycle (NCEP)
  - Cycling of errors captured
  - Estimates subspace of dynamically fastest growing errors in analysis
- ***Stochastic-dynamic approach*** – Perturbed Observations method (MSC)
  - Perturb all observations (given their uncertainty)
  - Run multiple analysis cycles
  - Captures full space (growing + non-growing) of analysis errors

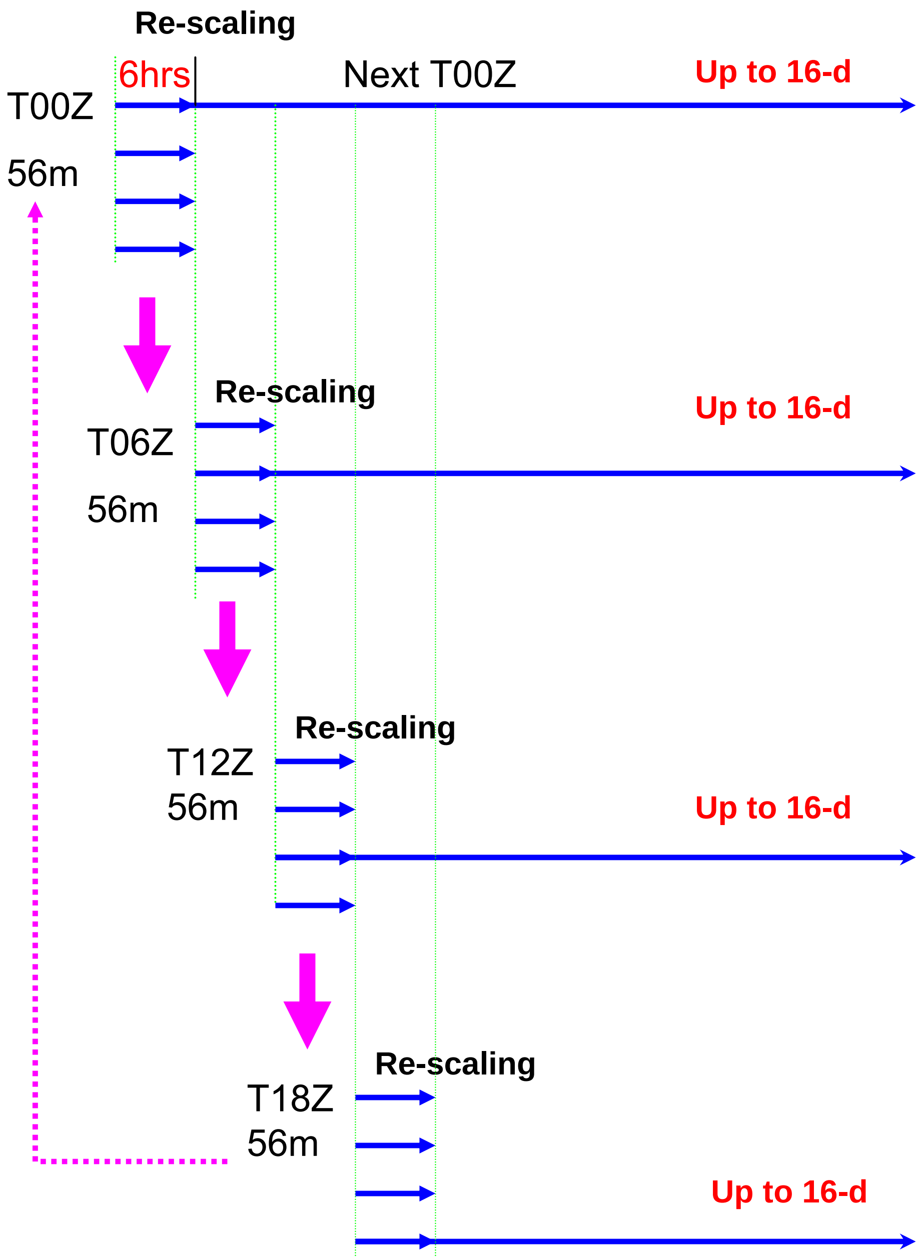
SAMPLING INITIAL CONDITION ERRORS

THREE APPROACHES – SEVERAL OPEN QUESTIONS

- **RANDOM SAMPLING** – **Perturbed observations method** (MSC)
  - Represents all potential error patterns with realistic amplitude
  - Small subspace of growing errors is well represented
  - Potential problems:
    - Much larger subspace of non-growing errors poorly sampled,
    - Yet represented with realistic amplitudes
- **SAMPLE GROWING *ANALYSIS* ERRORS** – **Breeding** (NCEP)
  - Represents dynamically growing analysis errors
  - Ignores non-growing component of error
  - Potential problems:
    - May not provide "wide enough" sample of growing perturbations
    - Statistical consistency violated due to directed sampling? Forecast consequences?
- **SAMPLE FASTEST GROWING *FORECAST* ERRORS** – **SVs** (ECMWF)
  - Represents forecast errors that would grow fastest in linear sense
  - Perturbations are optimized for maximum forecast error growth
  - Potential problems:
    - Need to optimize for each forecast application (or for none)?
    - Linear approximation used
    - Very expensive

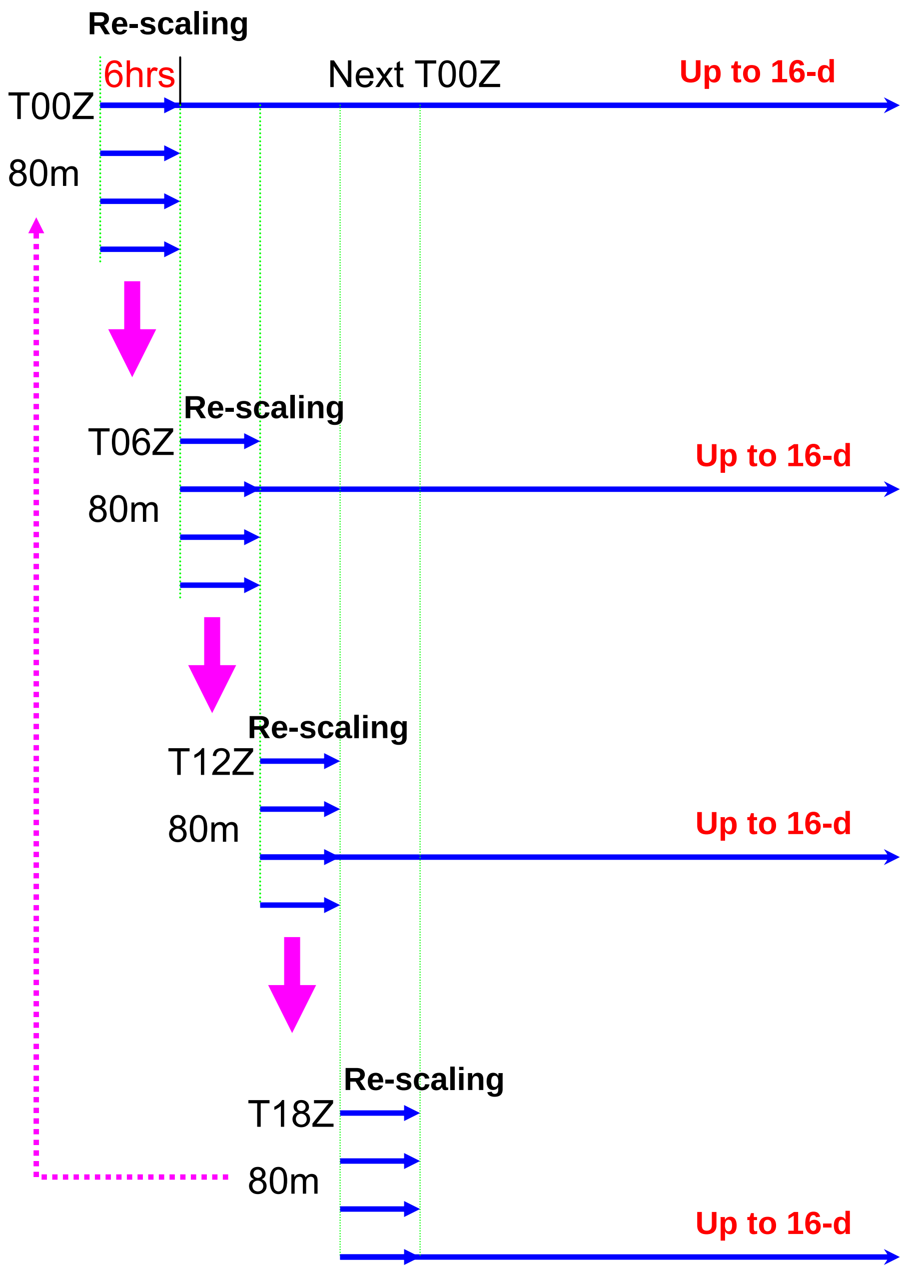
6 hours breeding cycle

Production



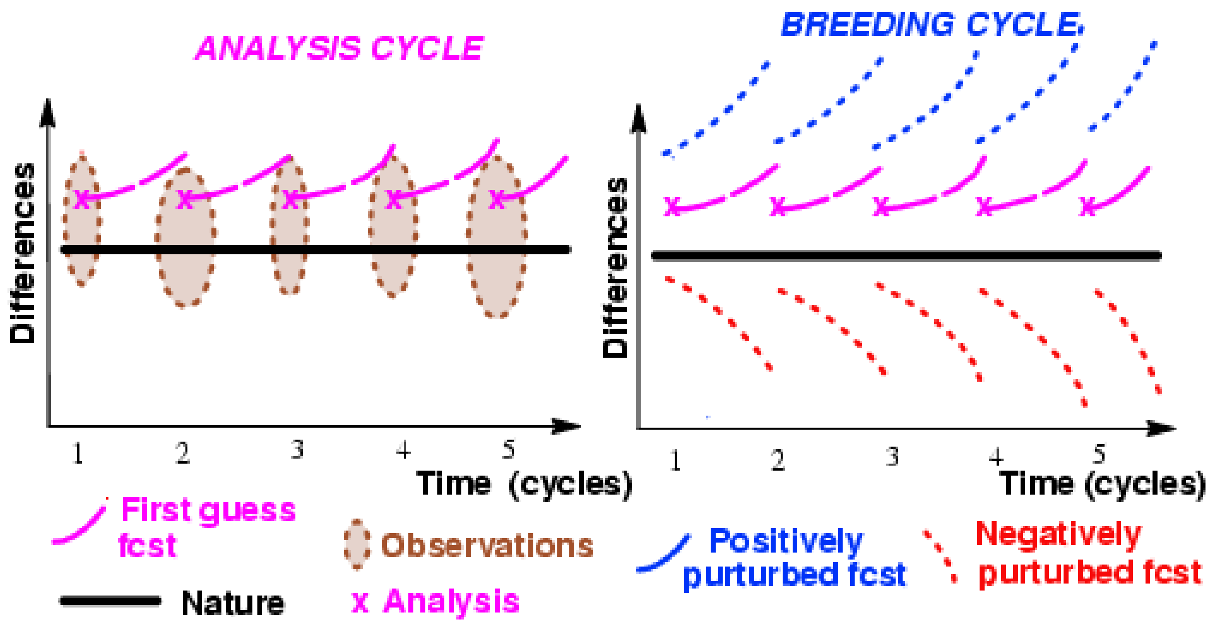
6 hours breeding cycle

Planned Change



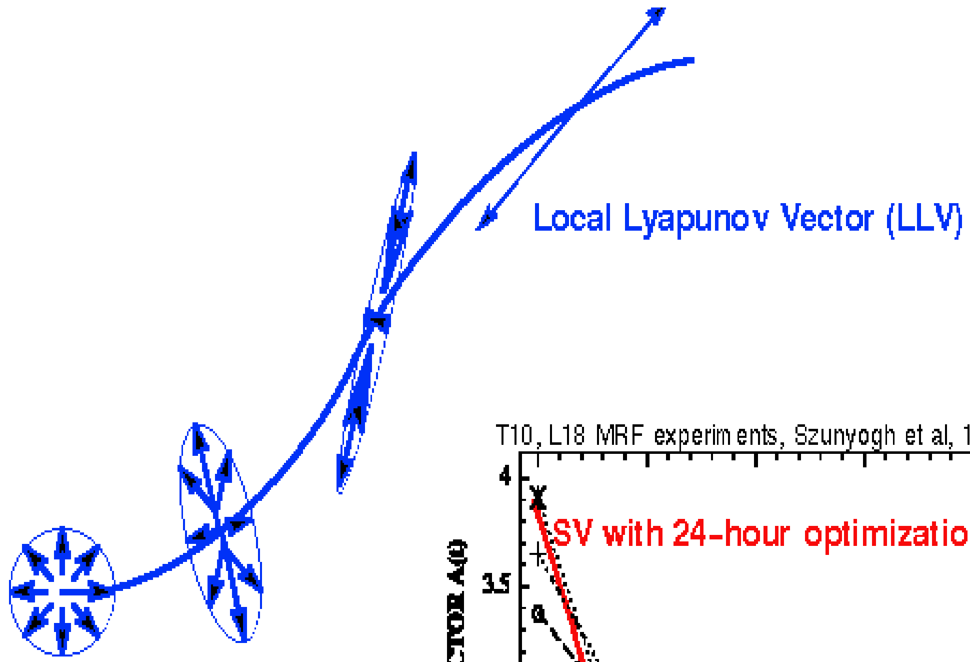
ESTIMATING AND SAMPLING INITIAL ERRORS: THE BREEDING METHOD

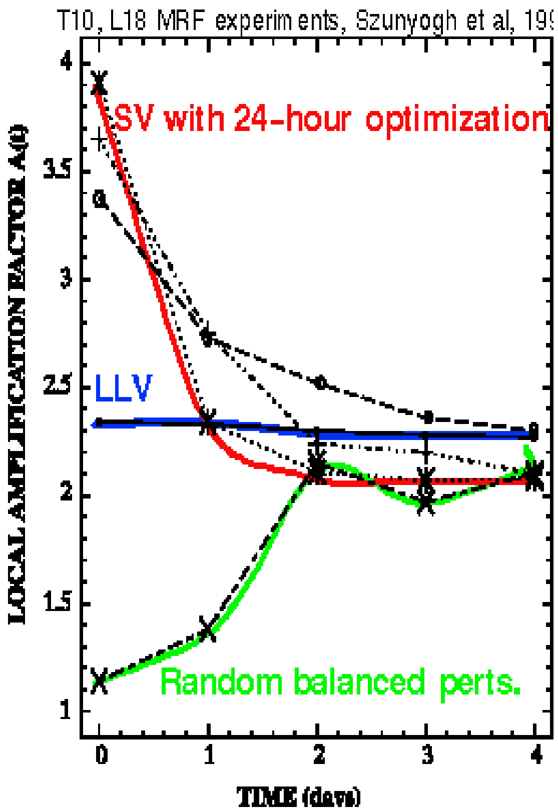
- **DATA ASSIM:** Growing errors due to cycling through NWP forecasts
- **BREEDING:** - Simulate effect of obs by rescaling nonlinear perturbations
  - Sample subspace of most rapidly growing analysis errors
    - Extension of linear concept of Lyapunov Vectors into nonlinear environment
    - Fastest growing nonlinear perturbations
    - Not optimized for future growth –
      - Norm independent
      - Is non-modal behavior important?



LYAPUNOV, SINGULAR, AND BRED VECTORS

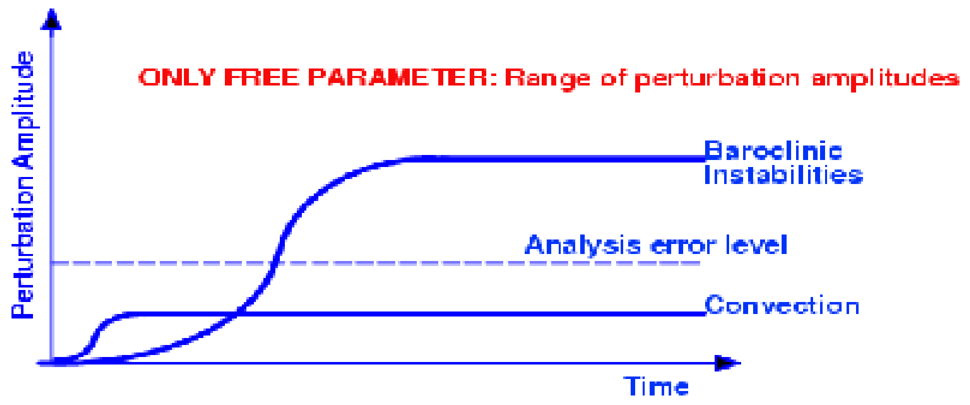
- **LYAPUNOV VECTORS (LLV):**
  - Linear perturbation evolution
  - Fast growth
  - Sustainable
  - Norm independent
  - Spectrum of LLVs
- **SINGULAR VECTORS (SV):**
  - Linear perturbation evolution
  - Fastest growth
  - Transitional (optimized)
  - Norm dependent
  - Spectrum of SVs
- **BRED VECTORS (BV):**
  - Nonlinear perturbation evolution
  - Fast growth
  - Sustainable
  - Norm independent
  - Can orthogonalize (Boffeta et al)





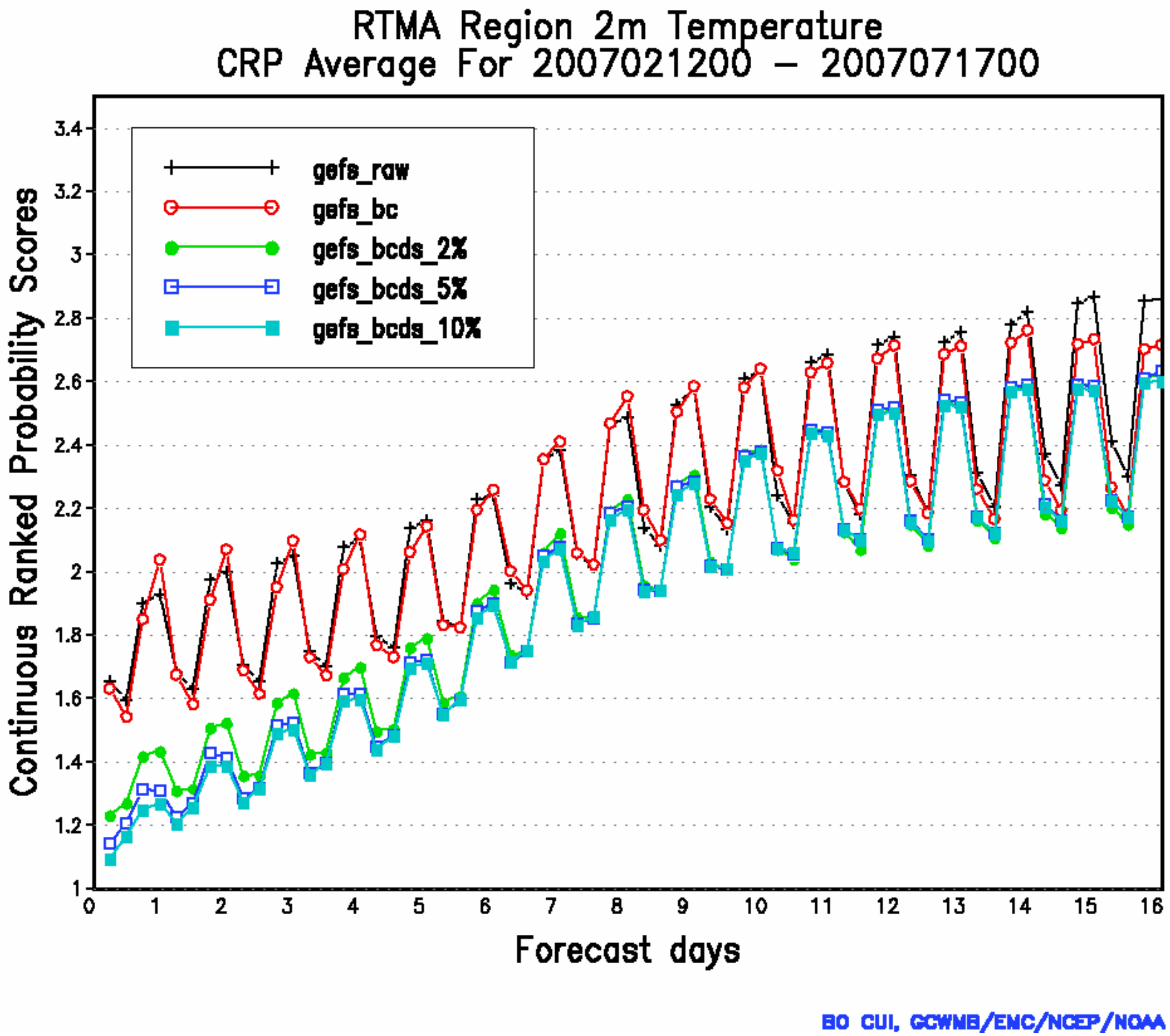
PERTURBATION EVOLUTION

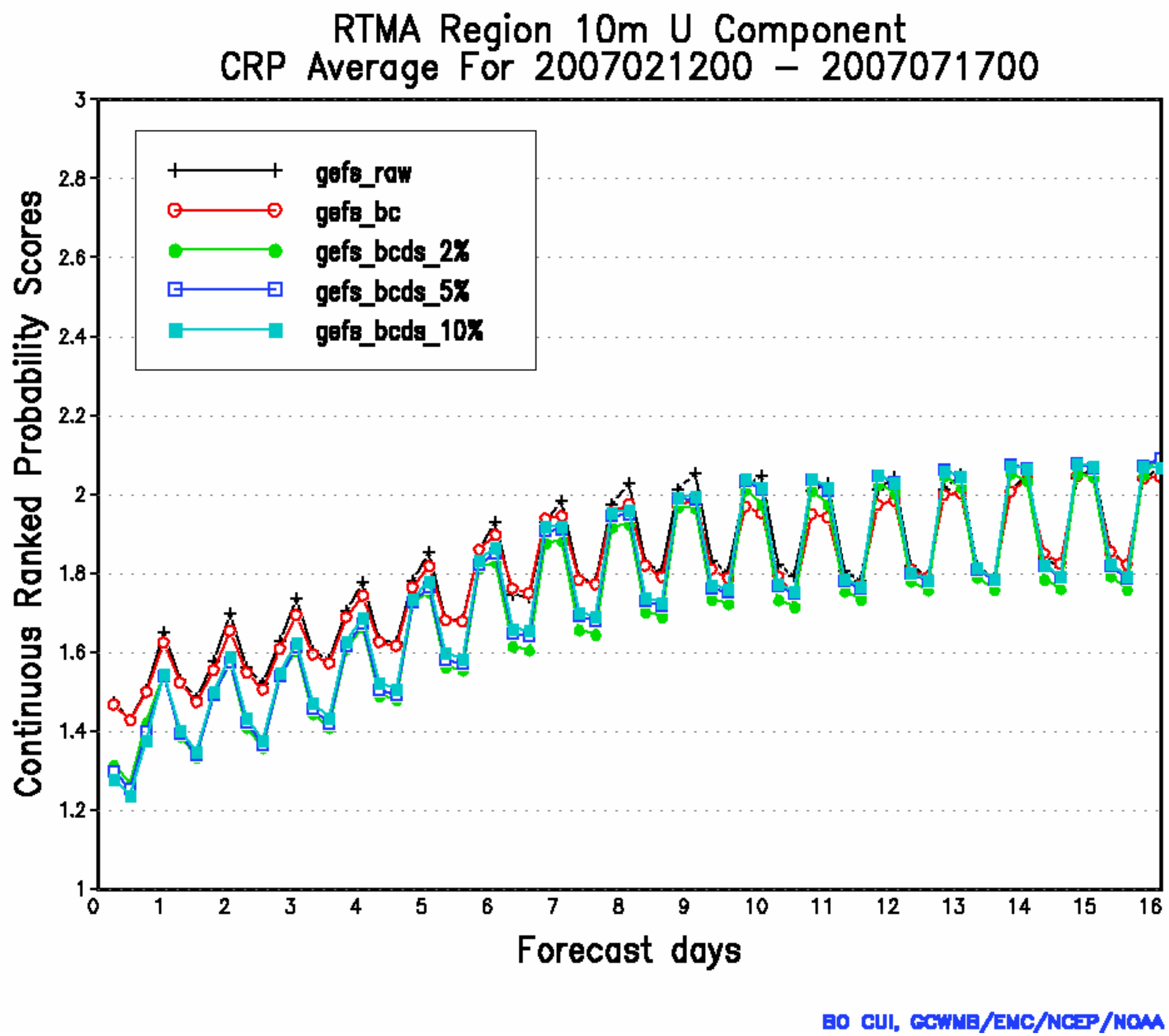
- **PERTURBATION GROWTH**
  - Due to effect of instabilities
  - Linked with atmospheric phenomena (e.g, frontal system)
- **LIFE CYCLE OF PERTURBATIONS**
  - Associated with phenomena
  - Nonlinear interactions limit perturbation growth
  - Eg, convective instabilities grow fast but are limited by availability of moisture etc
- **LINEAR DESCRIPTION**
  - May be valid at beginning stage only
  - If linear models used, need to reflect nonlinear effects at given perturb. Amplitude
- **BREEDING**
  - Full nonlinear description
  - Range of typic ... er



HOW TO REPRESENT INITIAL VALUE RELATED UNCERTRAINTY?

- Estimate analysis uncertainty
- Choices among sampling strategies, given an estimate
  - Monte Carlo type sampling – "Perturbed Observations" method
    - Run multiple analysis cycles with perturbed observations (Canadian approach).
    - Both growing and non-growing error space sampled with realistic amplitude.
    - Noise introduced hurts analysis performance.
  - Directed sampling
    - Singular vectors – fastest growth for pre-selected time period (ECMWF)
      - Transient growth emphasized.
      - Computationally very expensive.
      - No general solution: depending time interval and norm.
      - Norm most frequently used is uncoupled from analysis error estimates.
      - No success in DA applications.
    - Dynamical sampling in growing sub-space (NCEP)
      - Based on principle of breeding: Cycle growing perturbations
        - » Capture dynamics of system responsible for error growth.
        - » Ignore noise.
        - » Successfully used in most ensemble-based DA efforts: eg, ETKF, etc.


RTMA Region 2m Temperature
CRP Average For 2007021200 – 2007071700
gefs_raw
gefs_bc
gefs_bcds_2%
gefs_bcds_5%
gefs_bcds_10%
Continuous Ranked Probability Scores
Forecast days
3.4
3.2
3
2.8
2.6
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
BO CUI, GCWMB/EMC/NCEP/NOAA



RTMA Region 10m U Component
CRP Average For 2007021200 – 2007071700
Continuous Ranked Probability Scores
Forecast days
gefs_raw
gefs_bc
gefs_bcds_2%
gefs_bcds_5%
gefs_bcds_10%
3
2.8
2.6
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
BO CUI, GCWMB/EMC/NCEP/NOAA

CFS current operational configuration

Model	GFS version 2003 coupled with Ocean model MOM3 and ice climatology
Ensemble Method	*Lagged average*
Initial conditions	CDAS 2 for atmosphere, GDAS (7-days lag) for ocean
Coupling frequency	Once a day
Daily frequency	00 and 12 UTC
Resolution Atmos.	T62 L64
Resolution Ocean (74°S to 64°N)	1/3°´1° in tropics; 1°´1° in extratropics; 40 layers
Ensemble members	2 every day (60 per month)
Forecast length	10 months
Post-process	Bias correction Based on 24 yrs. of retrospective forecasts
Last implementation	August 2004

CFS Planned changes (Suru)

Model	GFS version 2007 coupled with Ocean model MOM4 and ice model
Ensemble Method	Lagged average
Initial Conditions	Coupled Reanalysis
Coupling frequency	Every hour
Daily frequency	00, 06, 12 and 18 UTC
Resolution Atmos.	T126 L64
Resolution Ocean (74°S to 64°N)	1/4°´1° in tropics; 1/2°´1/2° in extratropics; 40 layers
Ensemble members	4 every day
Forecast length	10 months
Post-process	Bias correction Based on retrospective forecasts
Planned implementation	2010

Computing analysis error variance from multi-center analysis data

One way to get 3-dimensional flow-dependent analysis error variance for generating initial ensemble perturbations in ET (Ensemble Transform) is to use different analysis fields from different NWP centers.

(a). Choose some common variables from the analysis data we have few different centers, such as NCEP, ECMWF, UKMET, MSM, JMA, US NAVY etc.

(b). Remove the systematic bias from each center’s analysis data by using a recursive filter.

(c). Compute the analysis error variance in kinetic energy or total energy norm using analysis data from different centers.

(d). Apply the 3-D analysis error variance to ET transformation and rescaling.

Deriving the analysis error variance from GSI

Another way to get 3-dimensional flow-dependent analysis error variance is from NCEP operational data assimilation system (GSI).

The method is based on Fisher and Courtier (1995), ECMWF Tech Memo. No. 220. It takes advantage of the connection between the conjugate gradient method which is being used in GSI and Lanczos method.

(a). Modify and run GSI to produce the gradient vectors from the preconditioned conjugate gradient method.

(b). Run an external program (independent of GSI operation) based on the Lanczos method to read the gradient files produced by GSI and generate the dominant eigenvectors and eigenvalues of the Hessian matrix.

(c). The analysis error covariance matrix will be reconstructed from the leading eigenvectors and eigenvalues of the Hessian which is the inverse of analysis error covariance.

(d) .The analysis error variances of GSI variables will need to be converted to those of model variables.

Analysis error variance used in ET and ET with rescaling

$\mathbf{P}_{op}^{a}$ is the analysis error variance obtained from operational GSI or from multi-center analysis data.

$$\mathbf{Z}^{f\,T}\mathbf{P}_{op}^{a\,-1}\mathbf{Z}^{f} = \mathbf{C}\,\mathbf{\Gamma}\,\mathbf{C}^{-1}$$

$$\mathbf{Z}^{f} = \frac{1}{\sqrt{(k-1)}}[\mathbf{z}_1^{f}, \mathbf{z}_2^{f}, \ldots\ldots, \mathbf{z}_k^{f}]$$

$$\mathbf{Z}^{a} = \frac{1}{\sqrt{(k-1)}}[\mathbf{z}_1^{a}, \mathbf{z}_2^{a}, \ldots\ldots, \mathbf{z}_k^{a}]$$

are fcst and analysis perturbati ons.

$$\mathbf{G} = \mathrm{diag}(\lambda_1, \ldots \lambda_2, \alpha), \qquad \alpha \neq 0, \qquad \mathbf{C} = [\mathbf{c}_1, \mathbf{c}_2, \ldots \mathbf{c}_k]$$

$$\mathbf{T}_p = \mathbf{CG}^{-1/2}, \qquad \mathbf{Z}_p^{a} = \mathbf{Z}^{f}\mathbf{T}_p = \mathbf{Z}^{f}\mathbf{CG}^{-1/2}$$

The transformed perturbations ($\mathbf{Z}_p^{a}$) are orthogonal with respect to an inverse analysis error variance. However, they are not centered. Centering will be done by a simplex transformation which preserves analysis error covariance.

For details, see Wei, Toth, Wobus and Zhu (2007), Initial perturbations based on the ensemble transform (ET) technique in the NCEP global operational forecast system, *Tellus A*, in print.

Finally, the transformed perturbations will be rescaled at multi-levels using the analysis error variance in the same way as in Toth and Kalnay (1993, 1997).

BACKGROUND - 2

THE MAKINGS OF A WEATHER FORECAST – *HOW FORECASTS ARE MADE?*

- Assess current weather situation
  - Before we can look into future, understand what is happening now
  - *"Initial condition"*

- Digest observational information
  - Bring observed data into "standard" format
  - *"Data assimilation"*

- Project initial state into future
  - Based on laws of physics
  - *"Numerical Weather Prediction"* (NWP) model forecasting

- Apply weather forecast information
  - Statistical post-processing
  - *"User applications"*

FORECASTS ARE NOT PERFECT – WHY?

SOURCES OF FORECAST ERRORS

IMPERFECT KNOWLEDGE OF

INITIAL CONDITIONS

- Incomplete observing system (not all variables observed)
- Inaccurate observations (instrument/representativeness error)
- Imperfect data assimilation methods
  - Statistical approximations (eg, inaccurate error covariance information)
  - Use of imperfect NWP forecasts (due to initial and model errors) –
  - Effect of cycling (forecast errors "inherited" by analysis – use breeding)

GOVERNING EQUATIONS:

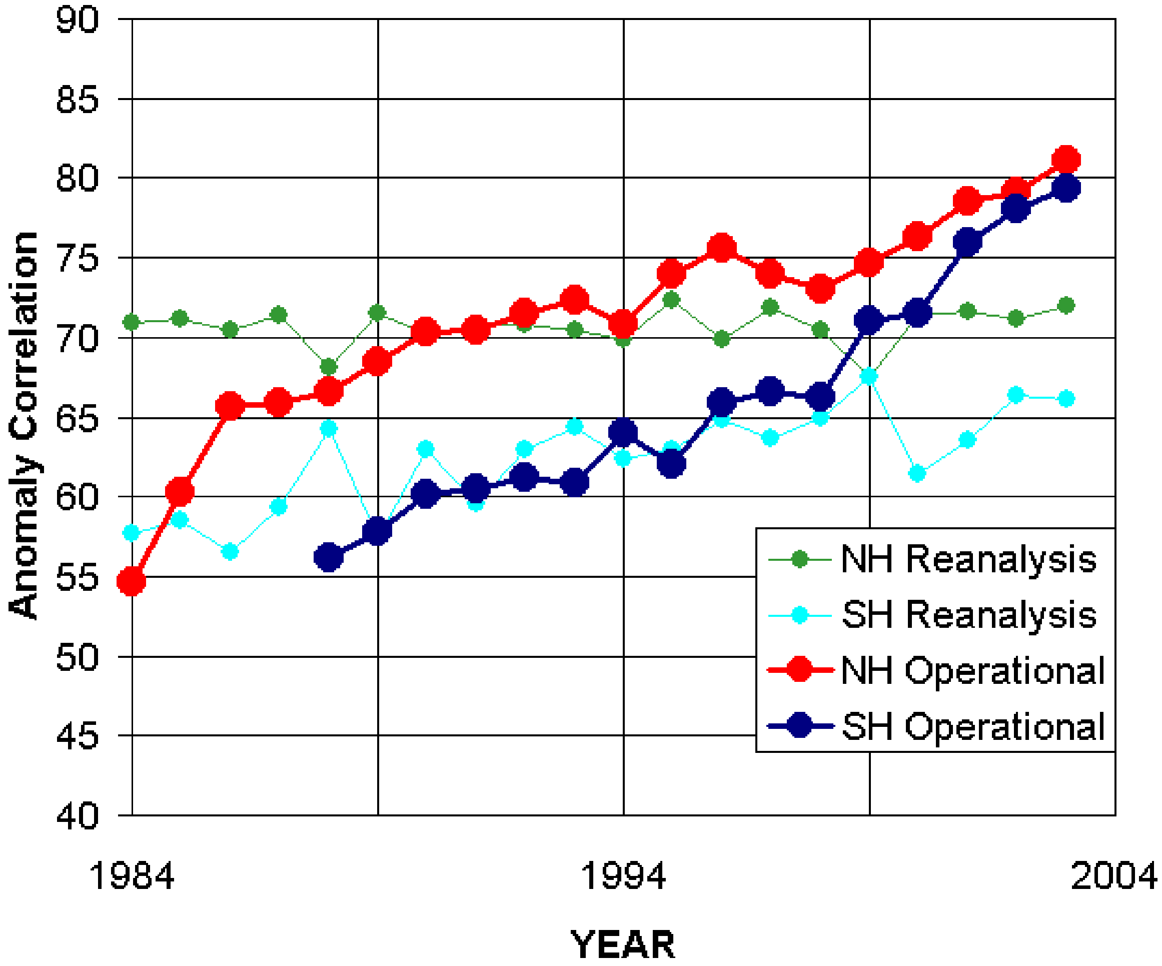
- Imperfect model
  - Structural uncertainty (eg, choice of structure of convective scheme)
  - Parametric uncertainty (eg, critical values in parameterization schemes)
  - Closure/truncation errors (temporal/spatial resolution; spatial coverage, etc)

NOTES:

- Two main sources of forecast errors hard to separate =>
- Very little information is available on model related errors
- Tendency to attribute all forecast errors to model problems

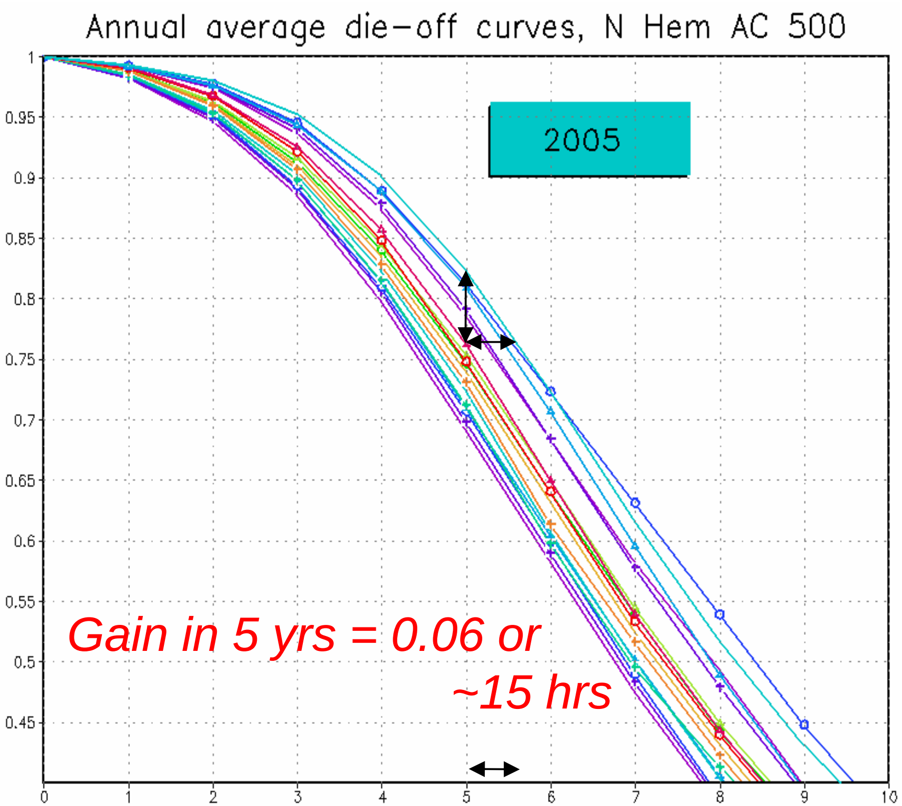
CAN REDUCE, BUT NEVER ELIMINATE ERRORS

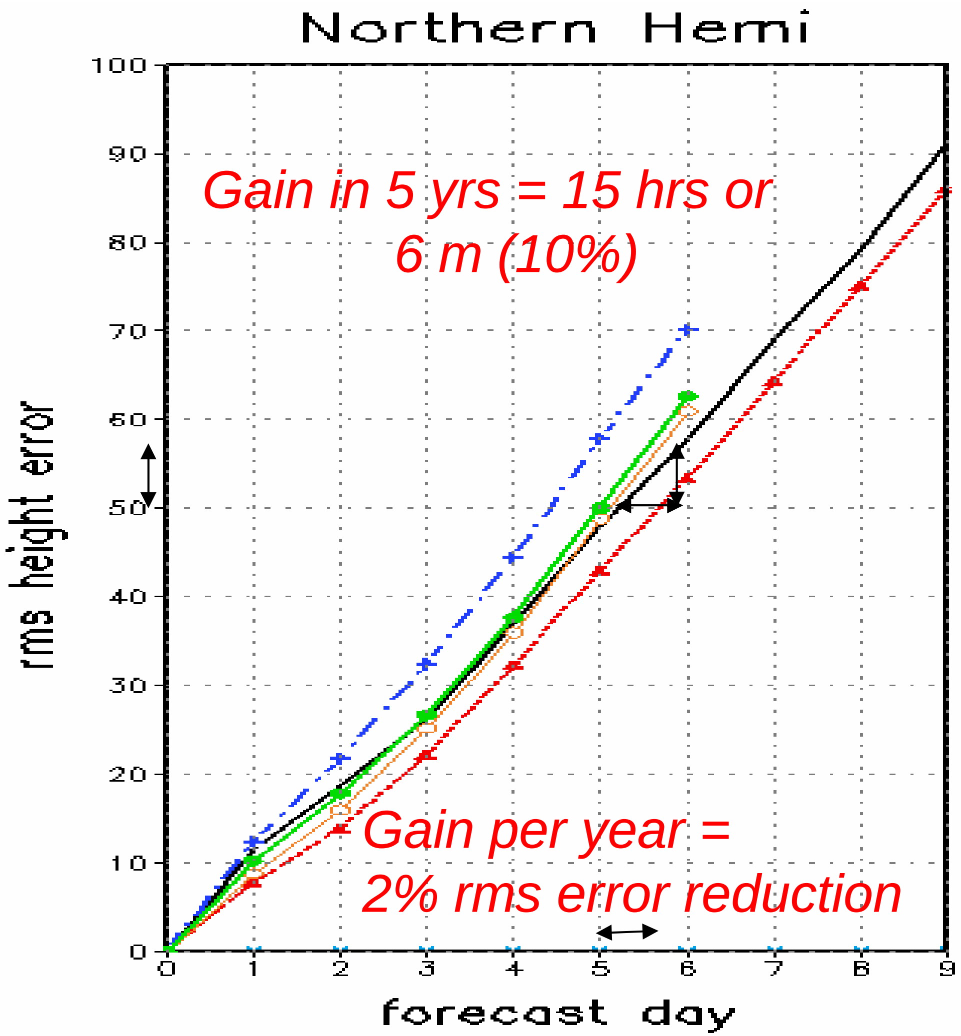
500 mb 5 Day Global Forecasts



EVER IMPROVING, BUT ALWAYS IMPERFECT – WHY?

WHY ERRORS AMPLIFY?





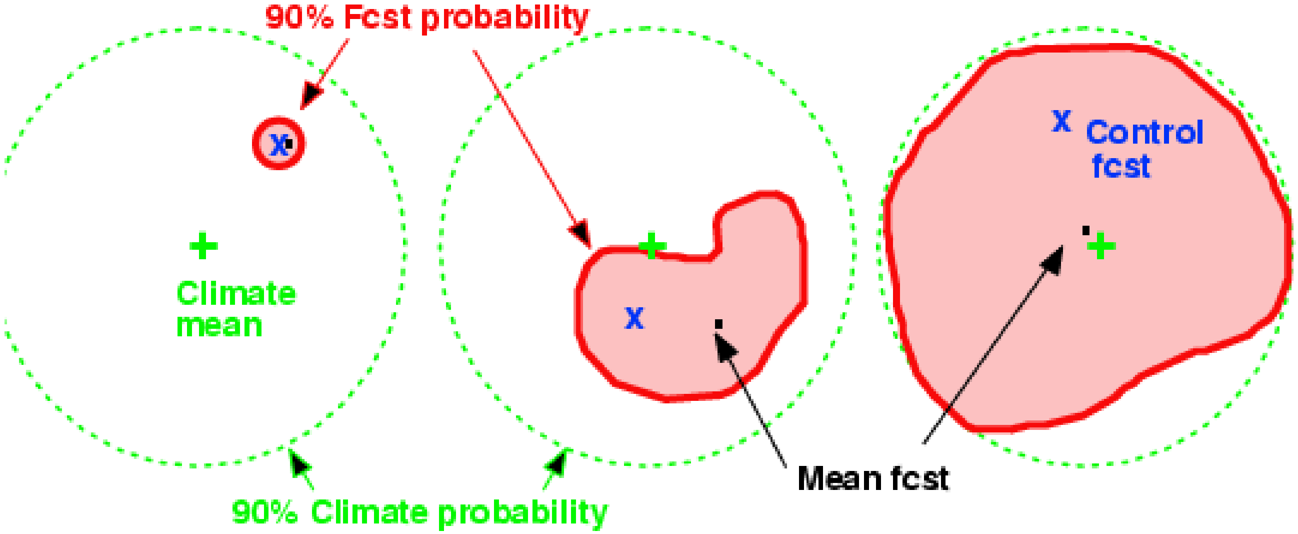
SCIENTIFIC NEEDS - DESCRIBE FORECAST UNCERTAINTY ARISING DUE TO CHAOS

ORIGIN OF FORECAST UNCERTAINTY

1) The atmosphere is a **deterministic system** *AND* has at least one direction in which **perturbations grow**

2) **Initial** state (and model) has **error** in it ==>

Chaotic system + Initial error =(Loss of) Predictability



Initial time

Day 5
Large uncretainty

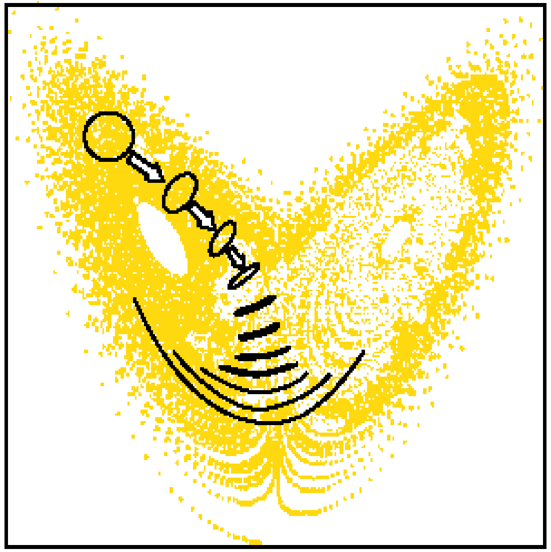
Day 12
Almost all predictability is lost – full nonlinear saturation

Ocean/Atm coupled system

5 months

12 months

Buizza 2002



VALUE OF PROBABILISTIC FORECASTING

- Potential economic value of probabilistic forecasts
  - "…the value of reliable – and even moderately unreliable – probabilistic forecasts generally exceeds the value of … categorical forecasts" - Murphy 1977

- Potential economic value of ensemble forecasts
  - "… a winder range of potential users can benefit from the ensemble than from the control forecasts … the ensemble offers more economic value than the control forecasts" – Zhu el al. 2002

- Operational forecasting implications
  - "…important implications for operational forecasting … desirability of formulating and disseminating a wide variety of weather forecasts in probabilistic terms…" Murphy 1977
  - "A weather forecast is … not complete unless it is expressed in the form of probability distributions." - Zhu el al. 2002
  - "Uncertainty is thus a fundamental characteristic of weather, climate, and hydrological prediction, and no forecast is complete without a description of its uncertainty." NRC Report: "Completing the Forecast", Ban et al., 2006

USER REQUIREMENTS:
PROBABILISTIC FORECAST INFORMATION IS CRITICAL

ECONOMIC VALUE OF FORECASTS

Given a particular forecast, a user either does or does not take action (eg, protects its crop against frost) *Mylne & Harrison, 1999*

		FORECAST	
		YES	*NO*
OBSERVATION	YES	H(its) ***Mitigated Loss***	M(isses) ***Loss***
	NO	F(alse alarms) ***Cost***	C(orrect rejections) ***No Cost***

$$\text{Mean Expense}_{fc} = hML + mL + fC$$

$$\text{Mean Expense}_{perf} = oML$$

$$ME_{cl} = \min[oL,\ oML + (1-o)C]$$

$$\text{Value} = \frac{ME_{cl} - ME_{fc}}{ME_{cl} - ME_{perf}}$$

o=climatological frequency

Optimum decision criterion for user action: P(weather event)=C/L

(Murphy 1977)

ASSESSING FORECAST UNCERTAINTY

- Forecast process has errors
  - Initial condition, model not perfect
- Errors can be reduced, but never eliminated
  - Main (only) NWP thrust so far: reduction of uncertainty
- Atmosphere is chaotic system
  - Any error amplifies
    - Predictability is finite and
      - Varies from case to case
- Users need to know about expected forecast errors
  - Serious limitation otherwise
- Errors can be assessed
  - Statistically
    - Climatology of errors in single forecast
  - Dynamically
    - Ensemble forecasts
      - ***New thrust in NWP is assessing uncertainty***

MOTIVATION FOR ENSEMBLE FORECASTING

- ***FORECASTS ARE NOT PERFECT* - IMPLICATIONS FOR:**
  - **USERS:**
    - Need to know how often / by how much forecasts fail
    - Economically optimal behavior depends on
      - Forecast error characteristics
      - User specific application
        - » Cost of weather related adaptive action
        - » Expected loss if no action taken
      - EXAMPLE: Protect or not your crop against possible frost

    Cost = 10k, Potential Loss = 100k => Will protect if P(frost) > Cost/Loss=0.1
    - ***NEED FOR PROBABILISTIC FORECAST INFORMATION***

  - **DEVELOPERS:**
    - Need to improve performance - *Reduce error in estimate of first moment*
      - Traditional NWP activities (I.e., model, data assimilation development)
    - Need to account for uncertainty - *Estimate higher moments*
      - New aspect – How to do this?
    - Forecast is incomplete without information on forecast uncertainty
    - ***NEED TO USE PROBABILISTIC FORECAST FORMAT***

FORECASTS ARE NOT COMPLETE UNLESS UNCERTAINTY ASSESSED

FORECASTING IN A CHAOTIC ENVIRONMENT

DETERMINISTIC APPROACH - PROBABILISTIC FORMAT

SINGLE FORECAST - *One integration with an NWP model*

- Is not best estimate for future evolution of system
  - Except if constrained by data in 4DVAR
- Does not contain all attainable forecast information
  - Case-dependent variations in forecast uncertainty missed
  - 4DVAR does not come with an ensemble generation algorithm
- Can be combined with past verification statistics to form probabilistic forecast
  - Gives **no estimate of flow dependent variations in forecast uncertainty**

PROBABILISTIC FORECASTING - *Based on Liuville Equations*

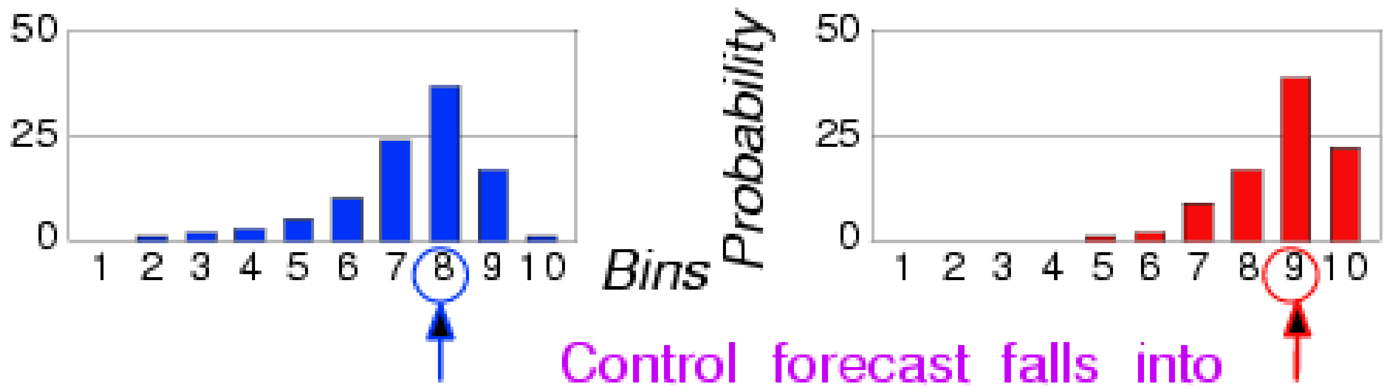
- Continuity equation for probabilities, given dynamical eqs. of motion
  - Dynamical forecast of pdf based on conservation of probability values
- Initialize with probability distribution function (pdf) at analysis time
- **Prohibitively expensive** -
  - Very high dimensional problem (state space x probability space)
  - Separate integration for each lead time
  - Closure problems when simplified solution sought

FORECASTING IN A CHAOTIC ENVIRONMENT –

PROBABILISTIC FORECASTING BASED A ON SINGLE FORECAST –

One integration with an NWP model, **combined with past verification statistics**

DETERMINISTIC APPROACH - PROBABILISTIC FORMAT



•Does not contain all forecast information

•Not best estimate for future evolution of system

•***UNCERTAINTY CAPTURED IN TIME AVERAGE SENSE -***

•**NO ESTIMATE OF CASE DEPENDENT VARIATIONS IN FCST UNCERTAINTY**

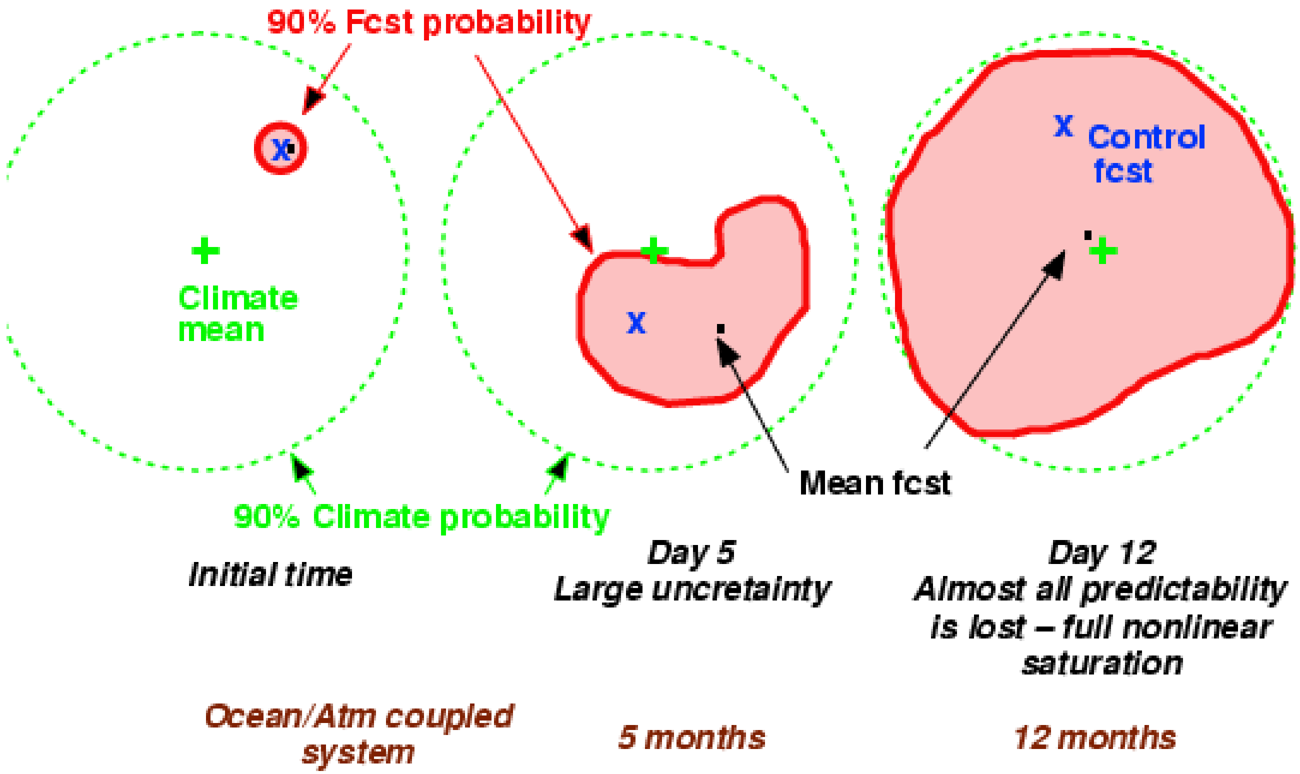
SCIENTIFIC NEEDS - DESCRIBE FORECAST UNCERTAINTY ARISING DUE TO CHAOS

ORIGIN OF FORECAST UNCERTAINTY

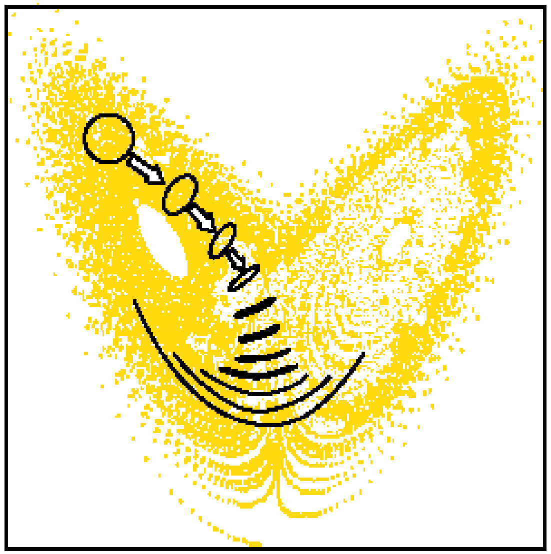
1) The atmosphere is a **deterministic system** *AND* has at least one direction in which **perturbations grow**

2) **Initial** state (and model) has **error** in it ==>

Chaotic system + Initial error =(Loss of) Predictability



Buizza 2002



WHY ENSEMBLES?

TRADITIONAL PARADIGM

- Single value forecast incomplete from viewpoints of
  - Science – Inherently statistically inconsistent with observations
  - Applications – Significantly fewer users, with less value
- Probabilistic forecasts needed – Generate them through
  - Single forecast integration
    - Accumulate error statistics over many cases (“bias correction”, eg, MOS)
    - Pro: Maximum possible fidelity in forecast - all comp. resources go into one solution
      - Improved statistical reliability; Slight increase in statistical resolution
    - Cons: Aggregate statistics - no case dependent variations in uncertainty captured
      As errors become nonlinear, single solution becomes unrepresentative
      - Loss of statistical resolution
  - Liouville equations
    - Theoretically proper solution in perfect model framework
      - Pdf of initial state integrated in time
        - » Impractical, enormous computational costs
  - Ensemble forecasts
    - Multiple integrations started with sample from estimated initial pdf
      - Provides multiple trajectories for critical downstream applications
    - Time evolution of pdf captured in truncated form (how many members needed?)
    - Ad-hoc methods aimed at capturing model related uncertainty

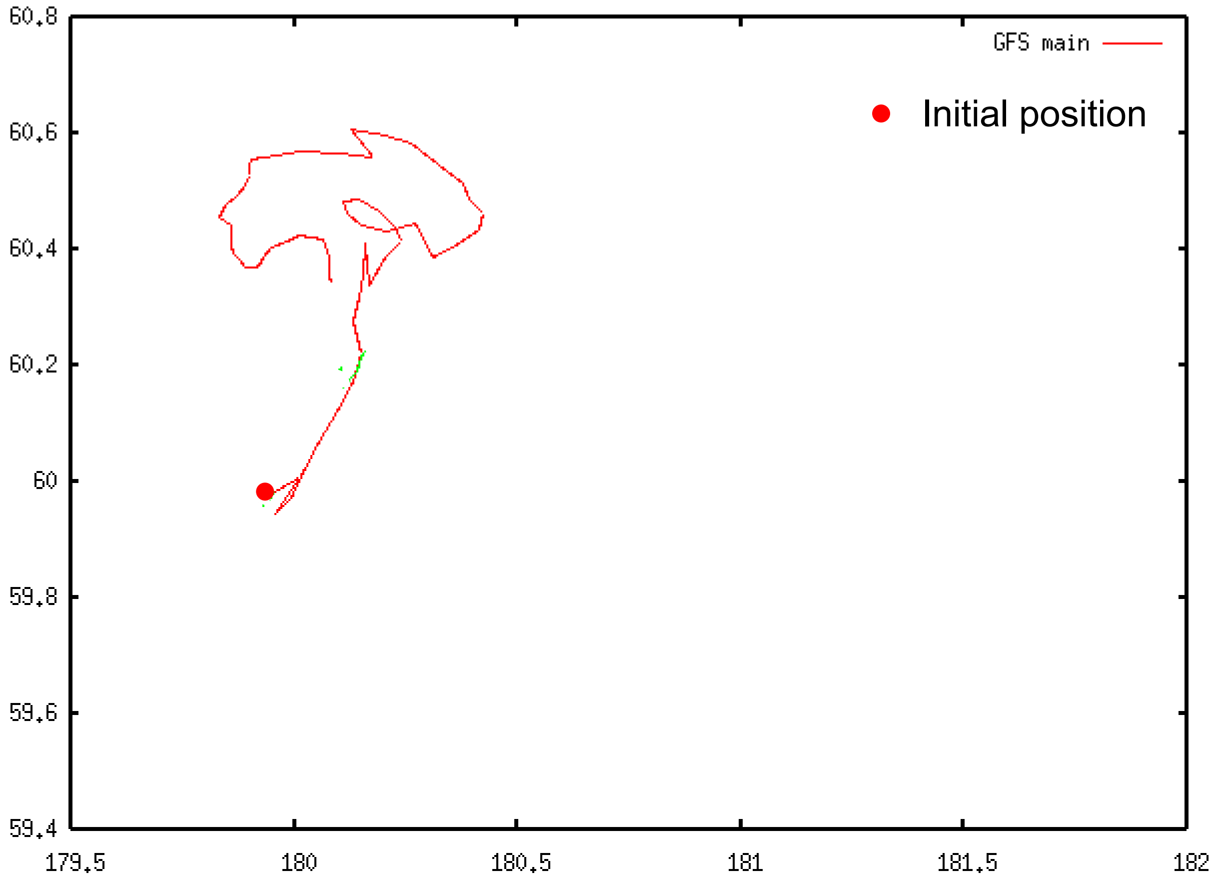
ENSEMBLE APPROACH

PROPOSED CHANGE

- Major paradigm shift
  - Incorporate assessment and communication of uncertainty in forecast process
- Is it a **major change in course** of “Weather Ship”?
  - Ie, abandon course of ever improving single forecast scenario (expected value)?
- No – Expand, not abandon
  - Keep improving fidelity of forecasts, PLUS
  - Add new dimension
    - Capture other possible scenarios – ensemble forecasting
      - Use a flotilla, instead of one ship, in exploring nature
  - Existing activities are subset of expanded forecast process
    - Single value forecast is expected value of full probability distribution
      - Can keep serving forecasts in old format to users who prefer that

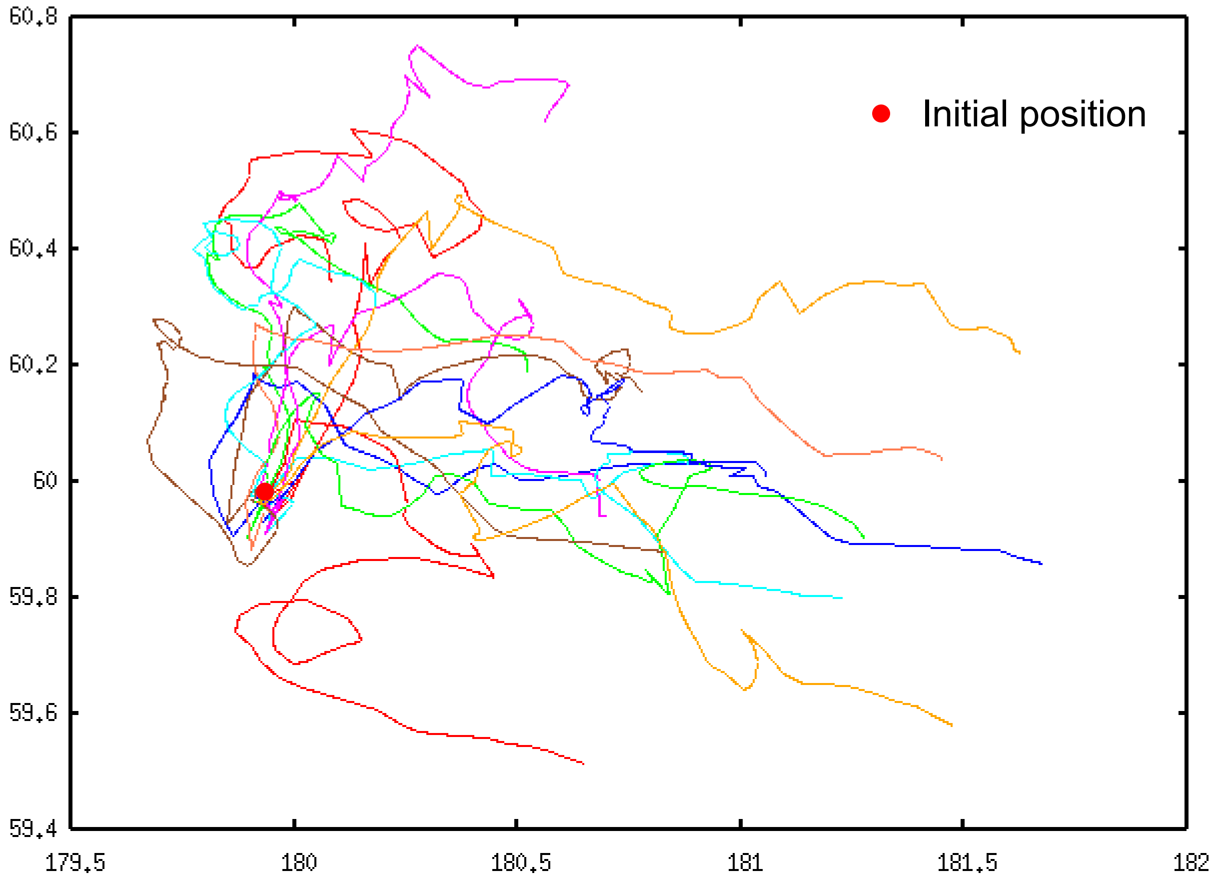
Single forecast (driven by GFS winds) example for drifting virtual ice floe

7 September 2006



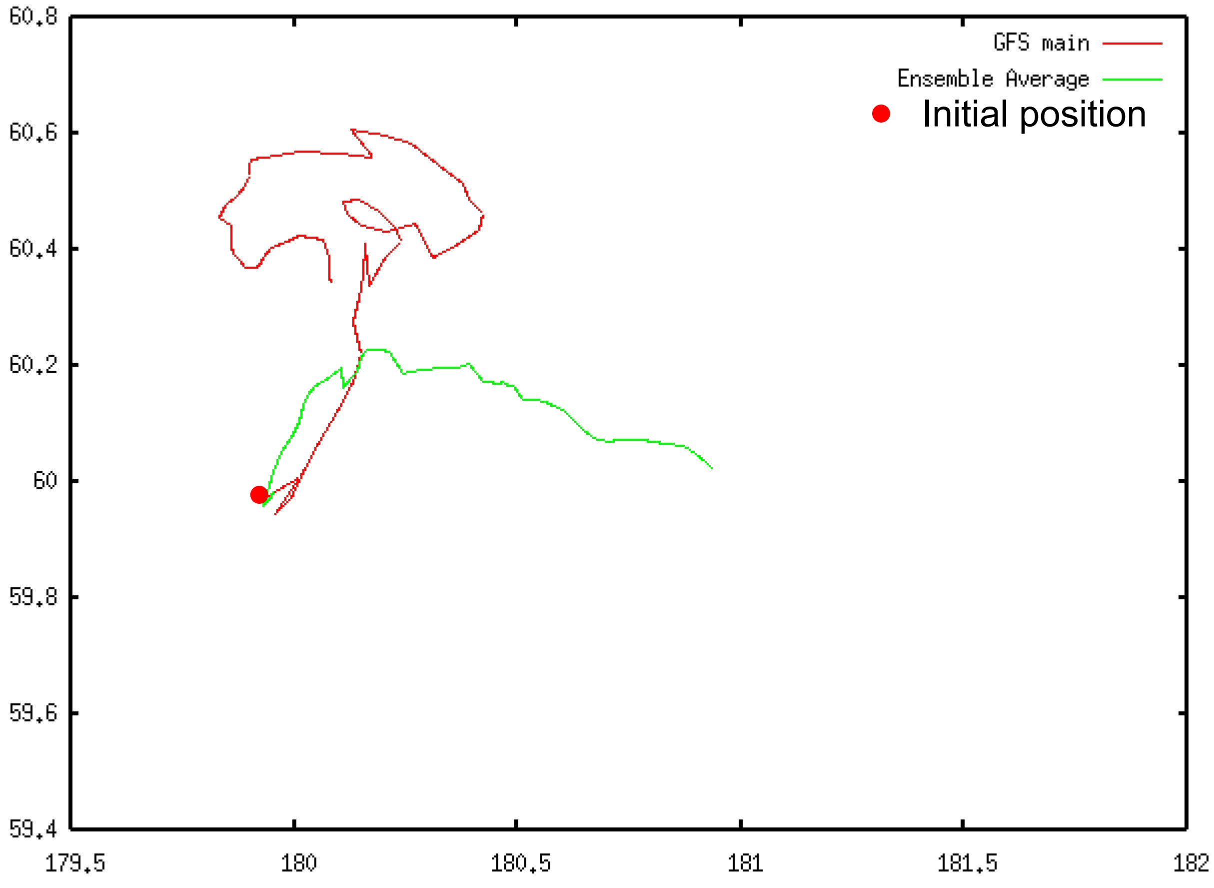
Bob Grumbine, EMC

Ensemble forecast for drifting ice floe for same case



Bob Grumbine, EMC

Most likely forecast for drifting ice floe for same case



Bob Grumbine, EMC

WHY CHANGE IS NEEDED?

- Why users (should) care about forecast uncertainty?
  - They admittedly want minimal or no uncertainty in forecasts
    - Distinction between no uncertainty in the forecast, vs. not talking about it
  - Forecast uncertainty cannot be arbitrarily reduced
    - Despite major ongoing & continuing efforts, they persist forever
      - Chaotic nature of atmosphere - land surface – ocean coupled system + initial/model errors
      - Level of uncertainty is determined by nature and level of sophistication in forecast system
  - Forecast uncertainty can be ignored though
    - Negative consequence on informed users
      - Not able to prepare for all possible outcomes
        - » Assumes a certain scenario and remains vulnerable to others
    - Possibly serious loss in social/economic value of forecast information

- Why forecasters (should) care about forecast uncertainty?
  - Imperfect forecasts are consistent w. observations (reliable) only if in prob format
    - If in other format, must be brought into probabilistic format through
      - Verification / bias correction

ADVANTAGES OF PROBABILISTIC FORMAT

- More rationalized and enriched forecaster - user interactions

  Old paradigm

  – Convoluted forecaster-user decision process
    - User expects forecaster to make decision for them in presence of uncertainty
      – “Will it rain?” – “80%” – “But tell me, will it rain?”

  New paradigm

  – Forecaster and user decision processes enhanced and better linked
    - Allows forecasters to capture all knowledge about future conditions
      – Provision of information related to multiple decision levels in probabilistic format critical
        » Provider helps interpret probabilistic info & and modify user decision process if needed
        » Option to continue providing single value or other limited info until user ready

    - Allows users to decide about most beneficial course of action given all possibilities
      – Proper use of probability or other uncertainty information needed - Training
        » User requests critical weather forecast info depending on their sensitivity

TRADITIONAL FORECAST PROCESS

- Focus on single forecast scenario
  - Reducing uncertainty in single forecast is main emphasis
    - Loss of accuracy in forecast estimate of expected value of distribution
      - Mean of ensemble cloud provides better estimate
  - Ignores or simplifies forecast uncertainty
    - Uncertainty assessed as statistically averaged error in single fcst (second thought)
      - Ensemble cloud provides better estimate of case dependent variations in uncertainty
  - Use of single value / categorical forecast format
    - Difficulty in formulating/communicating plausible alternate scenarios
      - Ensemble member forecasts can directly feed into Decision Support Systems

- One-way flow of information from observations to users
  - Not adaptable to case dependent user requirements
    - Ensemble can propagate back user requirements to adaptive
      - Observing, assimilation, modeling/ensemble, post-processing and application components
        - » Applications in planning and execution of new CONOPS in high impact events

PROPAGATING FORECAST UNCERTAINTY

OLD PARADIGM: Reduce Uncertainty	***FORECAST PROCESS***	**NEW PARADIGM:** Reduce & Assess Uncertainty
Misconstrued determinism	NATURE	Critical sensitivity to initial conditions - Chaos
Reduce obs. uncertainty	OBSERVING SYSTEM	Quantify obs. uncertainty
Estimate expected value	DATA ASSIMILATION	Estimate distribution
Reduce model errors	NWP MODELING	Reduce & represent model errors
Ad hoc opportunities	**ENSEMBLE FORECASTING**	Systematic approach
Reduce systematic error	STATISTICAL POST-PROCESSING	Calibrate uncertainty
Single value	BASIC PRODUCTS	Distributional characteristics
Yes or No forecasts tailored for decisions	USER SUPPORT SYSTEMS	Incorporate forecast uncertainty info
Limited forecast info - Restricted usage	SOCIETY	All forecast info – Optimal user decisions

Single value

Distribution

Ensemble Forecasting:
Central role – bringing the pieces together

HOW CAN IT BE DONE? NEW PARADIGM

- Adopt ensemble approach across all environmental prediction activities
  - Expand forecasting with new dimension of uncertainty
    - Multiple scenarios (in place of single scenario)
      - Provides best forecast estimate for both expected value (as before) and uncertainty (new)
  - Unified scientific, technological, human approach
    - Sharing resources across NWS & NOAA
  - Ensemble is centerpiece both symbolically and figuratively in forecast process
    - Ensembles act as a glue & two-way information channel
      - Observing system, data assimilation, numerical modeling
        - » ENSEMBLES
      - Statistical post-processing, product generation, decision making

- Design, develop, & implement missing components of new forecast process
  - Gradual, measured steps
    - Basic capability - Short-term, 2-3 yrs, leading to
    - Full implementation - Long-term, 5-10 yrs

FORECASTING IN A CHAOTIC ENVIRONMENT - 2

DETERMINISTIC APPROACH - PROBABILISTIC FORMAT

MONTE CARLO APPROACH – ***ENSEMBLE FORECASTING***

- ***IDEA*: Sample sources of forecast error**
  - Generate initial ensemble perturbations
  - Represent model related uncertainty

- ***PRACTICE*: Run multiple NWP model integrations**
  - Advantage of perfect parallelization
  - Use lower spatial resolution if short on resources

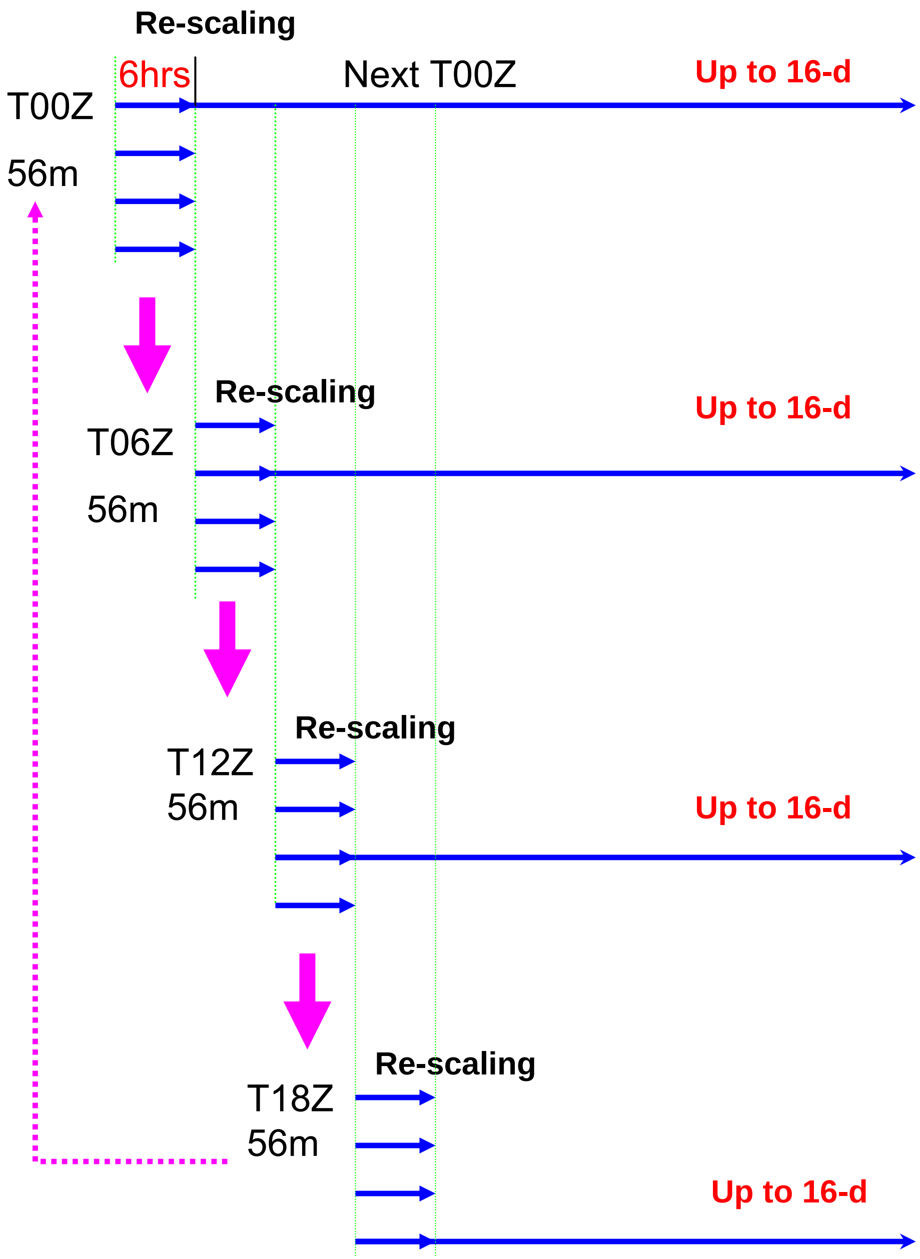
- ***USAGE*: Construct forecast pdf based on finite sample**
  - Ready to be used in real world applications
  - Verification of forecasts
  - Statistical post-processing (remove bias in 1st, 2nd, higher moments)

CAPTURES FLOW DEPENDENT VARIATIONS

IN FORECAST UNCERTAINTY

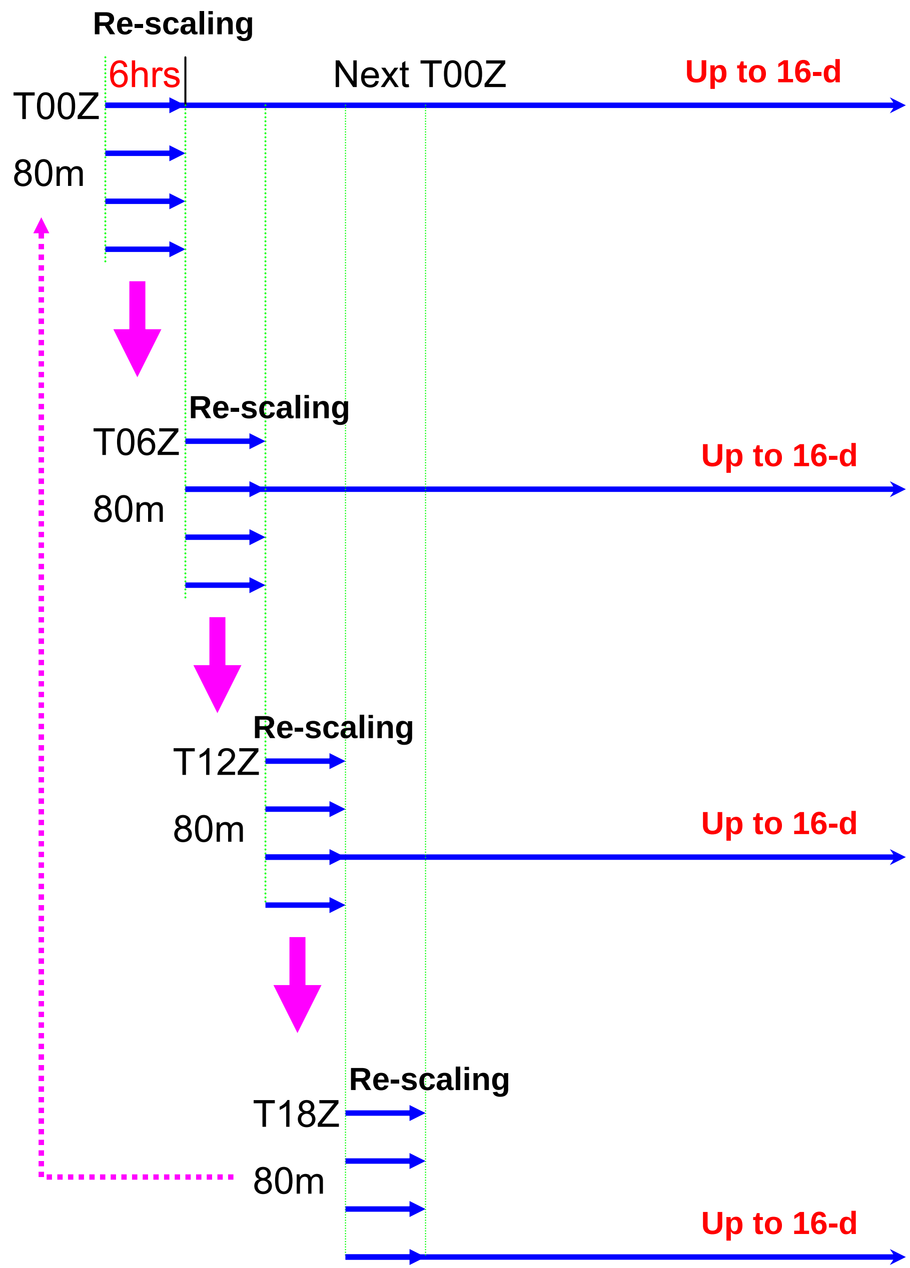
6 hours breeding cycle

Production



6 hours breeding cycle

Planned Change



SAMPLING FORECAST ERRORS =

REPRESENTING ERRORS ORIGINATING FROM TWO MAIN SOURCES

INITIAL CONDITION RELATED ERRORS – *"Easy"*

- Sample initial errors
- Run ensemble of forecasts
- It works
  - Flow dependent variations in forecast uncertainty captured (show later)
  - Difficult or impossible to reproduce with statistical methods

MODEL RELATED ERRORS – *No theoretically satisfying approach*

- Change structure of model (eg, use different convective schemes, etc, MSC)
- Add stochastic noise (eg, perturb diabatic forcing, ECMWF)
- Works? Advantages of various approaches need to be carefully assessed
  - Are flow dependent variations in uncertainty captured?
  - Can statistical post-processing replicate use of various methods?
- Need for a
  - more comprehensive and
  - theoretically appealing approach

SAMPLING INITIAL CONDITION ERRORS

CAN SAMPLE ONLY WHAT'S KNOWN – FIRST NEED TO

ESTIMATE INITIAL ERROR DISTRIBUTION

THEORETICAL UNDERSTANDING – THE MORE ADVANCED A SCHEME IS (e. g., 4DVAR, Ensemble Kalman Filter)

- The lower the overall error level is
- The more the error is concentrated in subspace of Lyapunov/Bred vectors

PRACTICAL APPROACHES –

ONLY SOLUTION IS MONTE CARLO (ENSEMBLE) SIMULATION

- ***Statistical approach*** (dynamically growing errors neglected)
    - Selected estimated statistical properties of analysis error reproduced
        - Baumhefner et al – Spatial distribution; wavenumber spectra
        - ECMWF – Implicite constraint with use of Total Energy norm
- ***Dynamical approach*** – Breeding cycle (NCEP)
    - Cycling of errors captured
    - Estimates subspace of dynamically fastest growing errors in analysis
- ***Stochastic-dynamic approach*** – Perturbed Observations method (MSC)
    - Perturb all observations (given their uncertainty)
    - Run multiple analysis cycles
    - Captures full space (growing + non-growing) of analysis errors

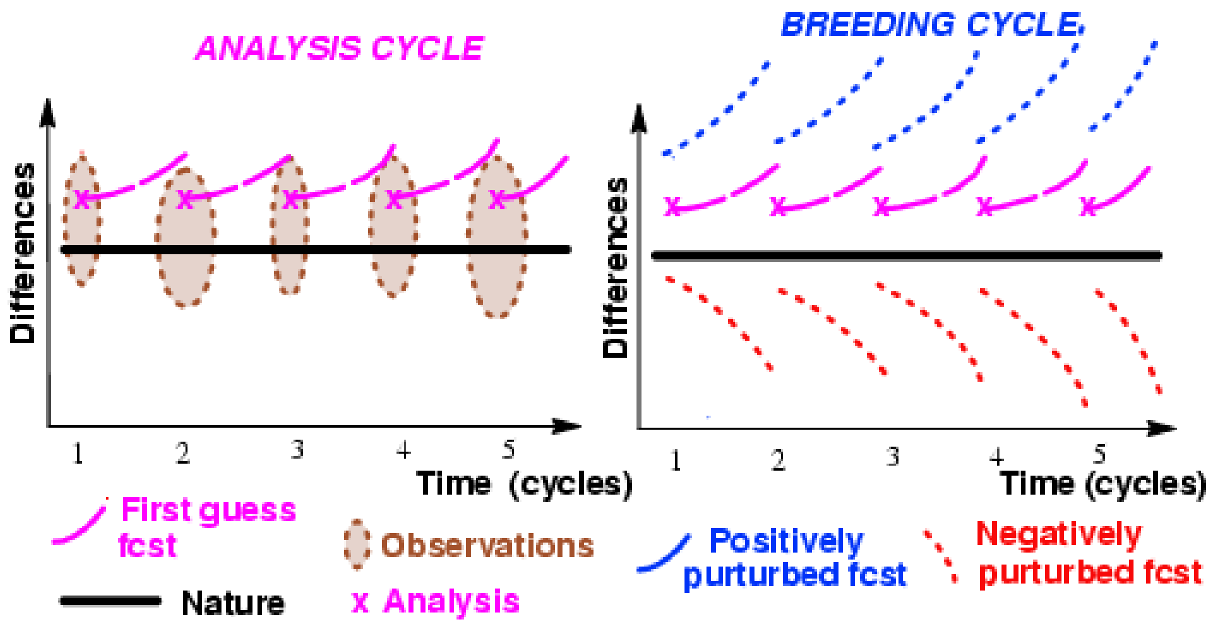
SAMPLING INITIAL CONDITION ERRORS

THREE APPROACHES – SEVERAL OPEN QUESTIONS

- **RANDOM SAMPLING** – **Perturbed observations method** (MSC)
  - Represents all potential error patterns with realistic amplitude
  - Small subspace of growing errors is well represented
  - Potential problems:
    - Much larger subspace of non-growing errors poorly sampled,
    - Yet represented with realistic amplitudes
- **SAMPLE GROWING *ANALYSIS* ERRORS** – **Breeding** (NCEP)
  - Represents dynamically growing analysis errors
  - Ignores non-growing component of error
  - Potential problems:
    - May not provide "wide enough" sample of growing perturbations
    - Statistical consistency violated due to directed sampling? Forecast consequences?
- **SAMPLE FASTEST GROWING *FORECAST* ERRORS** – **SVs** (ECMWF)
  - Represents forecast errors that would grow fastest in linear sense
  - Perturbations are optimized for maximum forecast error growth
  - Potential problems:
    - Need to optimize for each forecast application (or for none)?
    - Linear approximation used
    - Very expensive

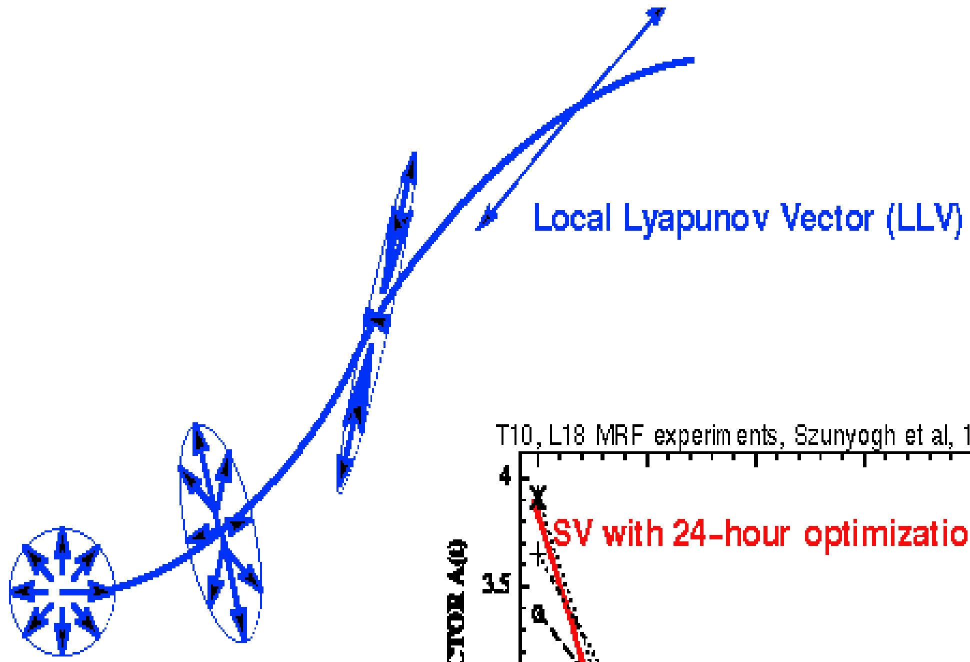
ESTIMATING AND SAMPLING INITIAL ERRORS: THE BREEDING METHOD

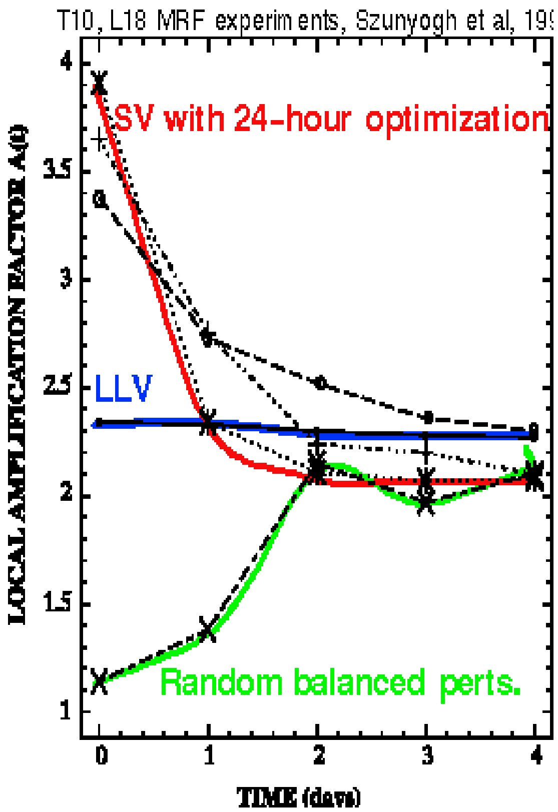
- **DATA ASSIM:** Growing errors due to cycling through NWP forecasts
- **BREEDING:** - Simulate effect of obs by rescaling nonlinear perturbations
  - Sample subspace of most rapidly growing analysis errors
    - Extension of linear concept of Lyapunov Vectors into nonlinear environment
    - Fastest growing nonlinear perturbations
    - Not optimized for future growth –
      - Norm independent
      - Is non-modal behavior important?



LYAPUNOV, SINGULAR, AND BRED VECTORS

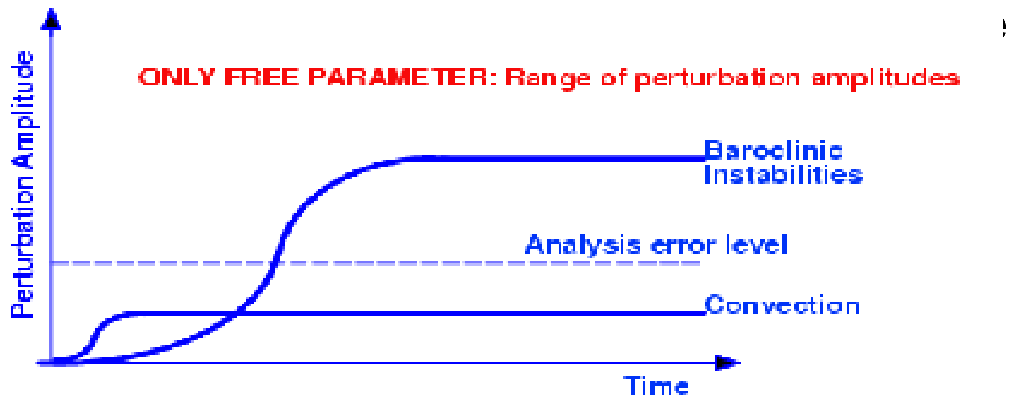
- **LYAPUNOV VECTORS (LLV):**
  - Linear perturbation evolution
  - Fast growth
  - Sustainable
  - Norm independent
  - Spectrum of LLVs
- **SINGULAR VECTORS (SV):**
  - Linear perturbation evolution
  - Fastest growth
  - Transitional (optimized)
  - Norm dependent
  - Spectrum of SVs
- **BRED VECTORS (BV):**
  - Nonlinear perturbation evolution
  - Fast growth
  - Sustainable
  - Norm independent
  - Can orthogonalize (Boffeta et al)





PERTURBATION EVOLUTION

- **PERTURBATION GROWTH**
  - Due to effect of instabilities
  - Linked with atmospheric phenomena (e.g, frontal system)
- **LIFE CYCLE OF PERTURBATIONS**
  - Associated with phenomena
  - Nonlinear interactions limit perturbation growth
  - Eg, convective instabilities grow fast but are limited by availability of moisture etc
- **LINEAR DESCRIPTION**
  - May be valid at beginning stage only
  - If linear models used, need to reflect nonlinear effects at given perturb. Amplitude
- **BREEDING**
  - Full nonlinear description
  - Range of typic ... r



HOW TO REPRESENT INITIAL VALUE RELATED UNCERTRAINTY?

- Estimate analysis uncertainty
- Choices among sampling strategies, given an estimate
  - Monte Carlo type sampling – “Perturbed Observations” method
    - Run multiple analysis cycles with perturbed observations (Canadian approach).
    - Both growing and non-growing error space sampled with realistic amplitude.
    - Noise introduced hurts analysis performance.

  - Directed sampling
    - Singular vectors – fastest growth for pre-selected time period (ECMWF)
      - Transient growth emphasized.
      - Computationally very expensive.
      - No general solution: depending time interval and norm.
      - Norm most frequently used is uncoupled from analysis error estimates.
      - No success in DA applications.

    - Dynamical sampling in growing sub-space (NCEP)
      - Based on principle of breeding: Cycle growing perturbations
        - » Capture dynamics of system responsible for error growth.
        - » Ignore noise.
        - » Successfully used in most ensemble-based DA efforts: eg, ETKF, etc.

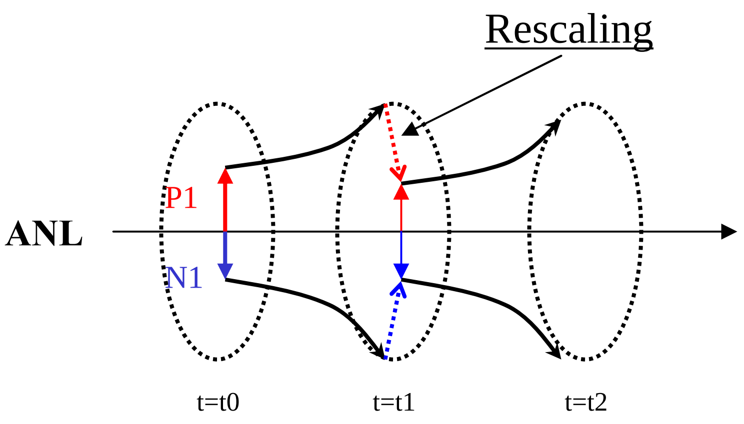
HOW TO REPRESENT INITIAL VALUE RELATED UNCERTRAINTY?

- **Proposed solution:** Dynamical sampling in growing sub-space – ET / ETKF

- Link with DA (GSI – ET)
  - Need collaboration between DA and ensemble teams.
  - Take error variance from GSI to specify ensemble perturbations
  - Feed back information from ensemble into background error covariance.
  - ET provides series of perturbed analyses consistent in time
    - Important for wave, land surface ensembles etc where perts depends on the history.

- Ensemble-based DA – ETKF
  - Same ensemble principles, except 2-way interactions tuned simultaneously.

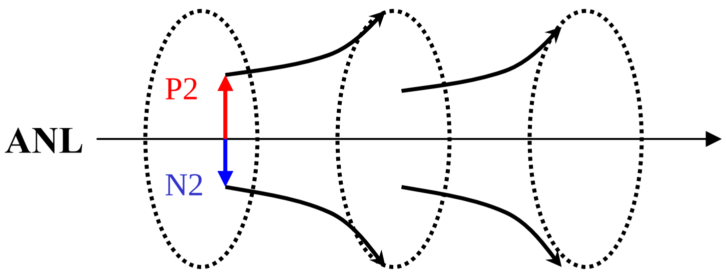
Bred Vector
(Current)



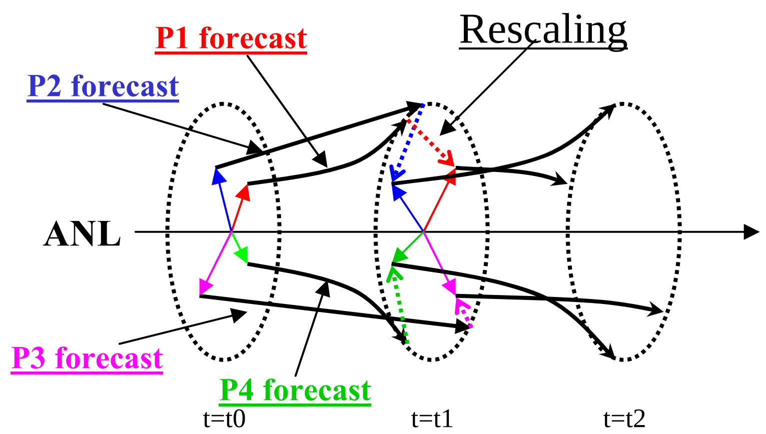
P#, N# are the pairs of positive and negative

P1 and P2 are independent vectors

Simple scaling down (no direction change)



Ensemble Transform Bred Vector
(New)



P1, P2, P3, P4 are orthogonal vectors

No pairs any more

To centralize all perturbed vectors (sum of all vectors are equal to zero)

Scaling down by applying mask,

The direction of vectors will be tuned by ET.

Unified EFS and DA

- *EFS and DA systems must be consistent for best performance of both.*
- SSI/GSI currently *provides best estimate of analysis, GSI will be used to derive analysis uncertainties (error variance) for EFS.*
- *EFS produces flow dependent forecast (background) error covariance to be tested in GSI later.*

A Hybrid DA-EFS System

GSI

Best analysis error variances $(diag(\mathbf{P}^a))$ →

← Accurate forecast error covariance $\mathbf{P}^f$ or $\mathbf{B}$

EFS

4. Summary of Perturbation Properties

(a). Perts are centered around the analysis to improve ensemble mean.

(b). They have simplex structure, not paired. Ensures that perts will have maximum number of effective degrees of freedom. The variance will be maintained in as many directions as possible within the ensemble subspace.

(c). They are uniformly centered and distributed in different directions. The larger the ensemble, the more orthogonal they become. They become orthogonal if the number of members approaches to infinity.

(d). The initial perts have flow dependent spatial structure if the analysis error variance is derived from operational DA system at every cycle.

(e). The covariance constructed from the perts is approximately consistent with the analysis covariance from the DA if the number of ensemble members is large.

References: Wei *et al.* 2005, ***WMO TD No.1237***, **WWRP THORPEX No. 6**, 2005. p227-230.
2006, **US Department of Commerce, NOAA/NCEP Office Note 453**, 33pp, September 2006, (also submitted to Tellus A, 2007).

	Perturbed Observations (MSC, Canada)	Breeding with Regional Rescaling (NCEP, USA)	Singular Vectors with total energy norm (ECMWF)
Estimation of analysis uncertainty	Realistic through sample, case dependent patterns and amplitudes.	Fastest growing subspace, case dependent patterns.	No explicit estimate used, variance not flow dependent.
Sampling of analysis uncertainty	Random for all errors, including non-growing, potentially hurts short-range performance.	Nonlinear Lyapunov vectors, subspace of fastest growing errors, some dependence among perturbations.	Dynamically fastest growing in future, orthogonal.
Consistency between EFS and DA system	Good, quality of DA lagging behind 3D-Var.	Not consistent, time-constant variance due to use of fixed mask.	Not consistent, potentially hurting short-range performance.

	ETKF, perturbations influenced by forecasts and observations	ET/rescaling with analysis error variance estimate from DA	Hessian Singular Vectors
Estimation analysis uncertainty	Fast growing subspace, case dependent patterns and amplitudes.	Fast growing subspace, case dependent patterns and amplitudes.	Case-dependent variance info from analysis, amplitudes of SVs have to be specified.
Sampling analysis uncertainty	Orthogonal in the normalized observational space.	High EDF in ensemble subspace.	Dynamically fastest growing in future.
Consistency between EFS and DA system	Very good, however, quality of DA has not been proven better than 4D-Var in operational environment so far.	Very good, DA provides good analysis for EFS which provides accurate forecast error covariance for DA.	Possibly consistent (not used operationally by any known NWP centres).

SOURCES OF FORECAST ERRORS

IMPERFECT KNOWLEDGE / REPRESENTATION OF

GOVERNING LAWS

USE OF IMPERFECT MODELS LEADS TO:

- Closure/truncation errors related to:
    - Spatial resolution
    - Time step
    - Type of physical processes explicitly resolved
    - Parameterization scheme chosen
        - Structure of scheme
        - Choice of parameters
    - Geographical domain resolved
        - Boundary condition related uncertainty (Coupling)

NOTES:

- Two main (initial cond. vs. model) sources of forecast errors hard to separate =>
- Very little information is available on model related errors
- Tendency in past to attribute all forecast errors to model problems

Houtekamer, Buizza, Smith, Orrell, Vannitsem, Hansen, etc

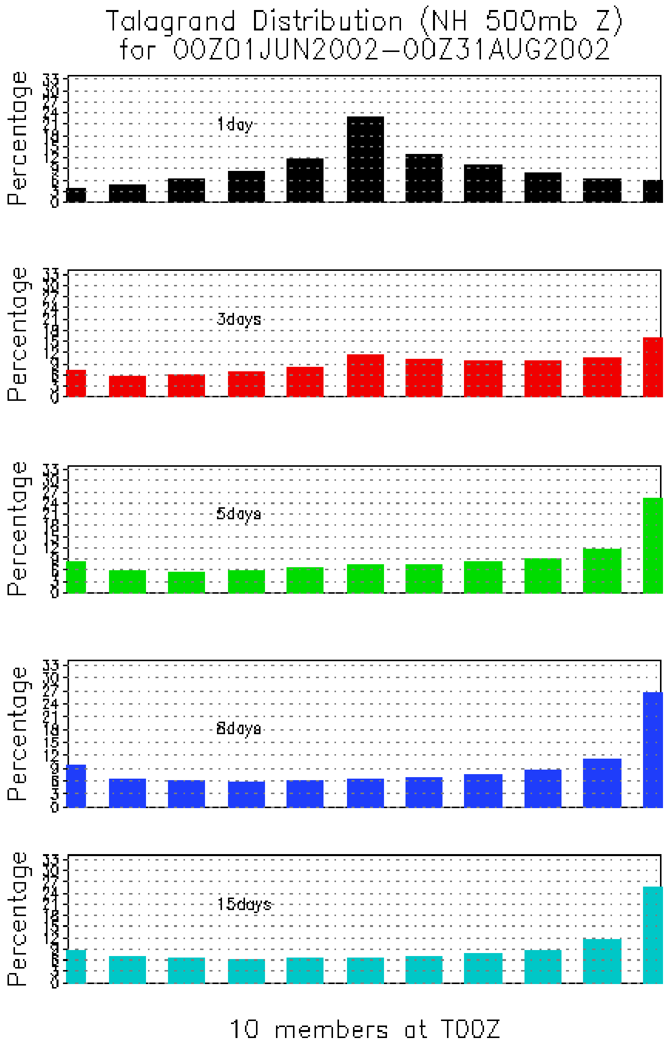
WHAT HAPPENS IF MODEL ERRORS ARE IGNORED?

Y. Zhu

NCEP ENSEMBLE RESULTS:

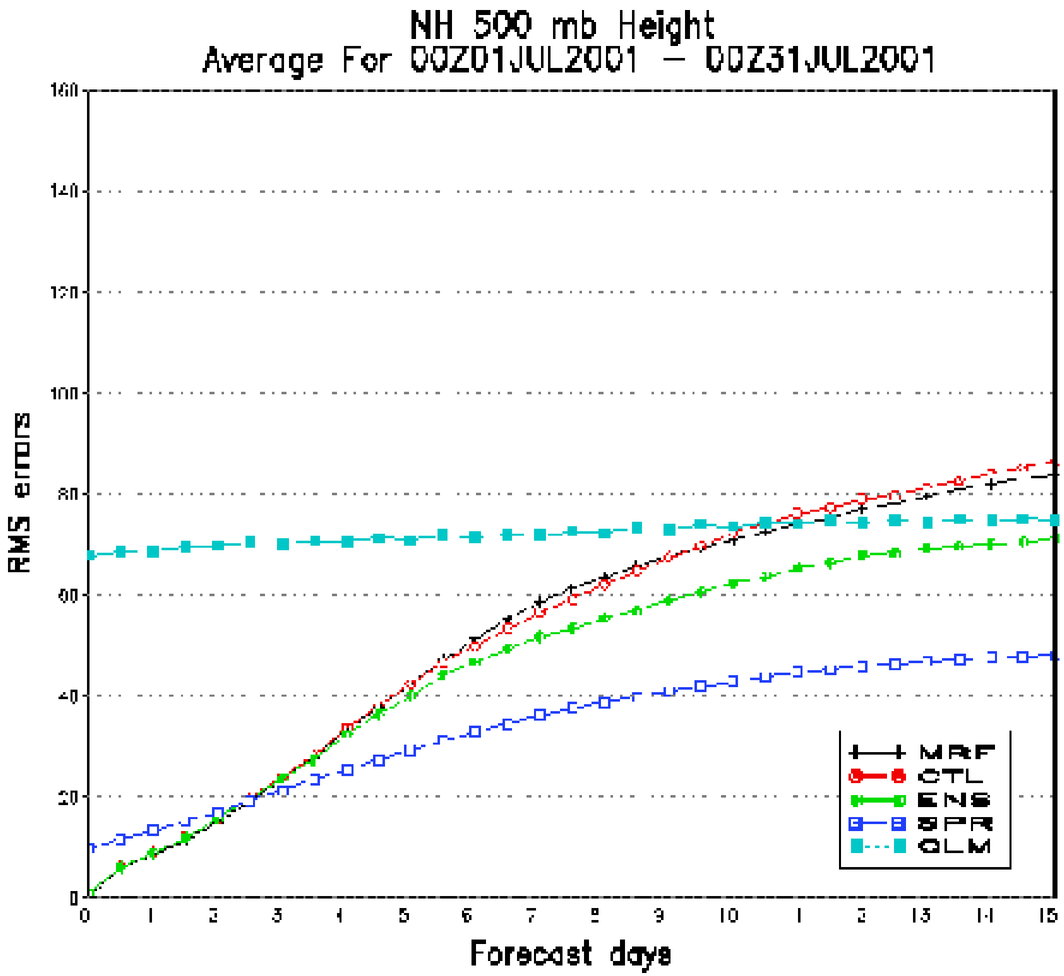
Bias in first moment

All members shifted statistically



Bias in second moment

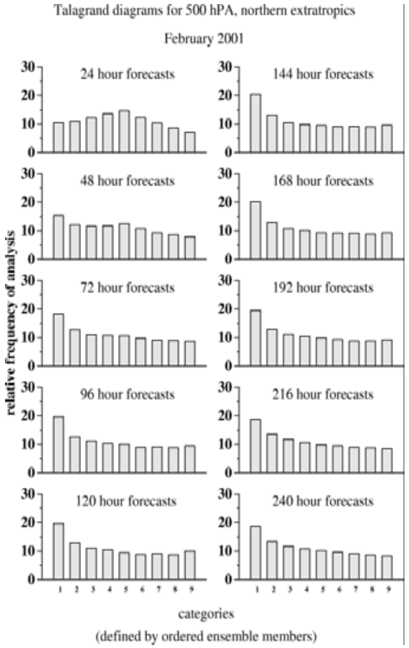
Perturbation growth lags error growth



The impact of using a second model at MSC

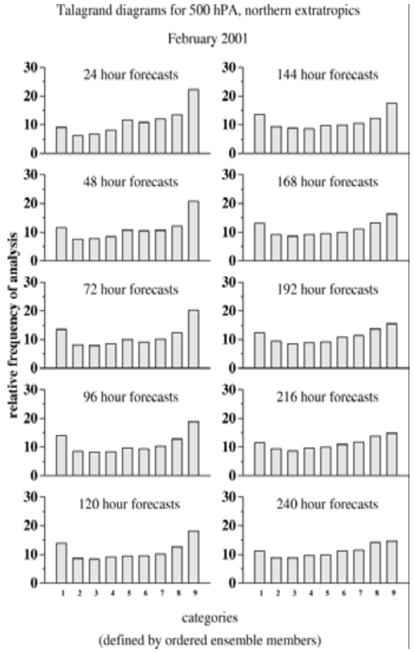
The warm bias was reduced substantially and the U-shape disappeared by combining the two ensembles into the 16-SEF/GEM ensemble.

8-SEF



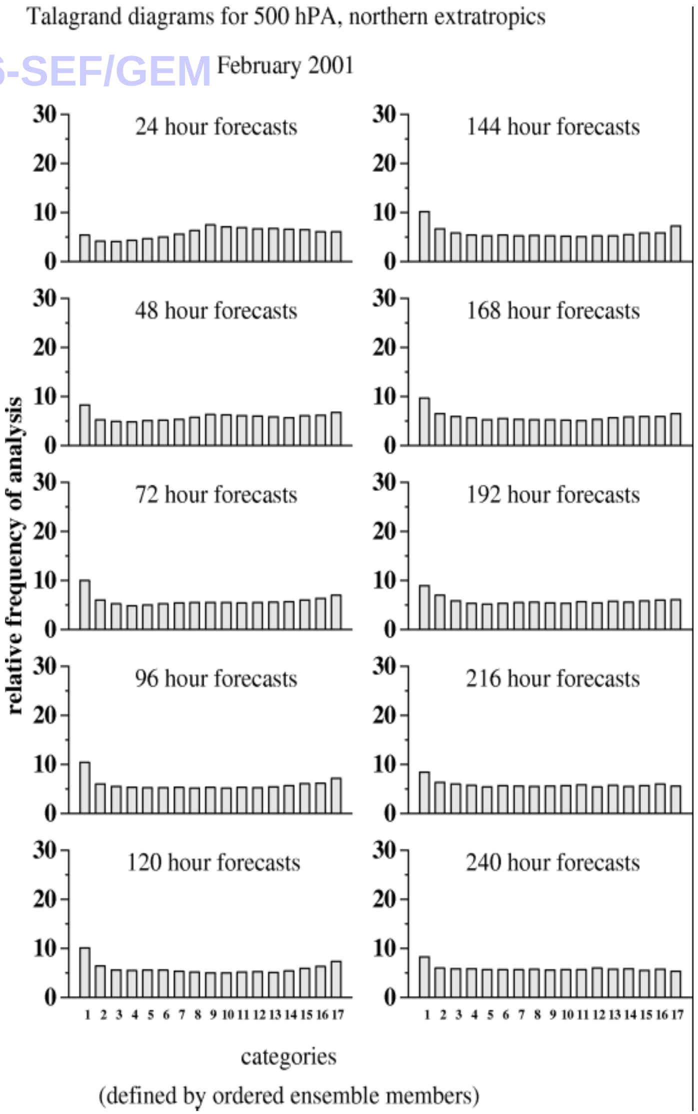
⊕

8-GEM



=

16-SEF/GEM



P. Houtekamer

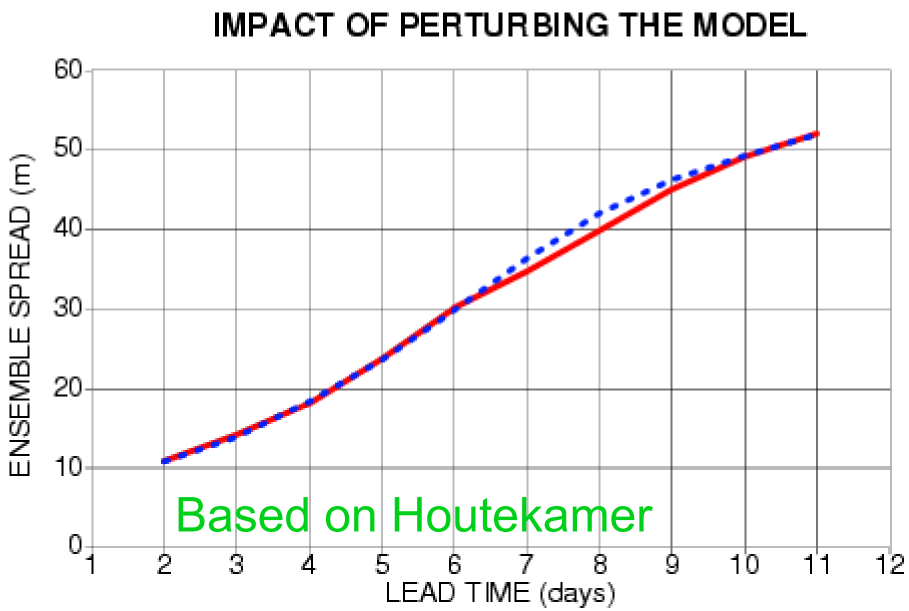
SAMPLING FORECAST ERRORS =

REPRESENTING ERRORS DUE TO USE OF

IMPERFECT MODELS - 1

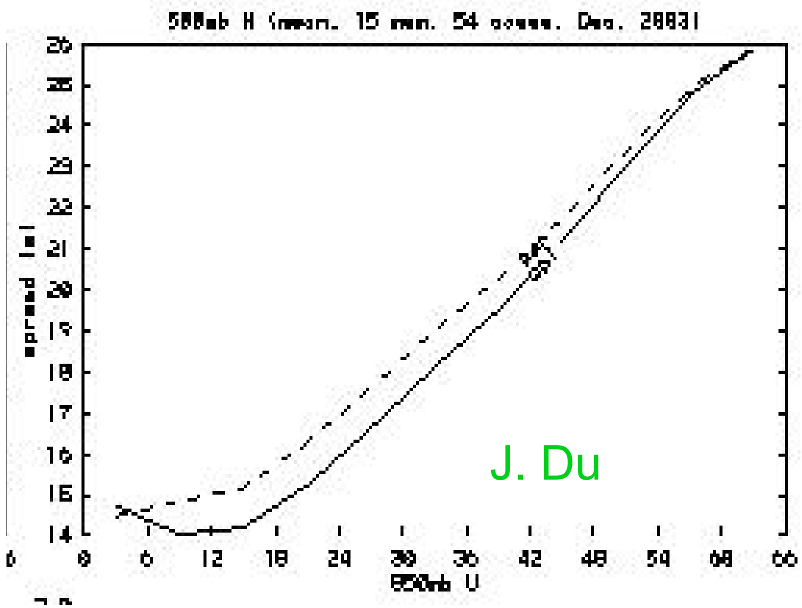
CURRENT METHODS

1) **Change structure of model (use different convective schemes, etc, MSC)**
   - Perturbation growth not affected?
   - Biases of different model versions cancel out in ensemble mean?



Spread of 8–member ensemble with (blue dashed line) and without (red continuous line) changing model parameters/physics packages from one ensemble member to the another. 500 hPa geopotential height, forecasts started at 0000 UTC on April 18, 1994. Note that initial perturbations are larger for thechanging model ensemble and that the curve for the unchanging model ensemble has been shifted one day to the left, to illustrate that in this ensemble setup the chages in model configuration do not result in larger spread. Data are from Table 4 of Houtekamer et al., 1996.

Spread

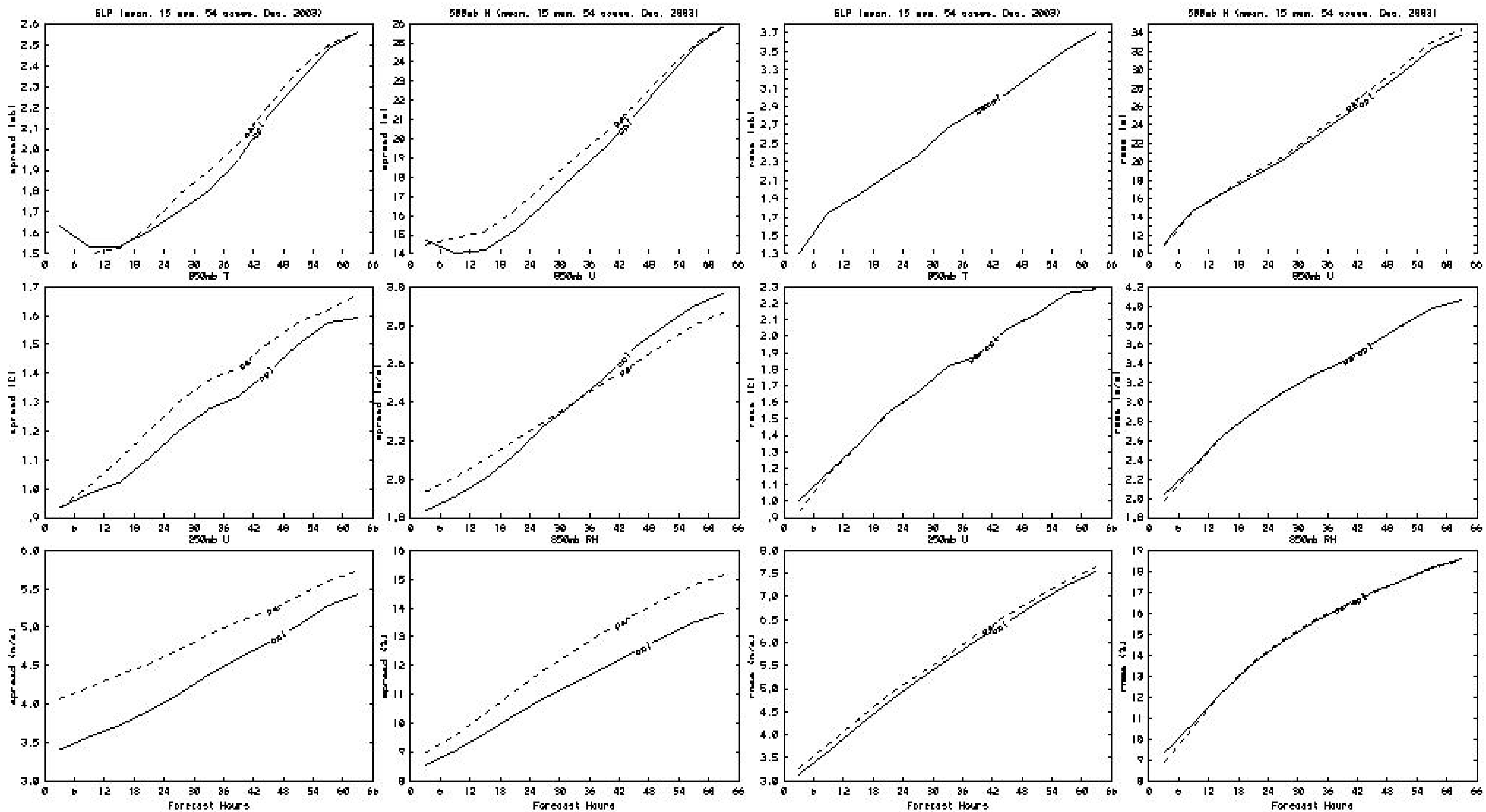


Oper: 3 model versions
Para: More model diversity

Oper: 3 model versions (ETA, ETA/KF, RSM)
Para: More model diversity

Spread

RMS error



SAMPLING FORECAST ERRORS =

REPRESENTING ERRORS DUE TO USE OF

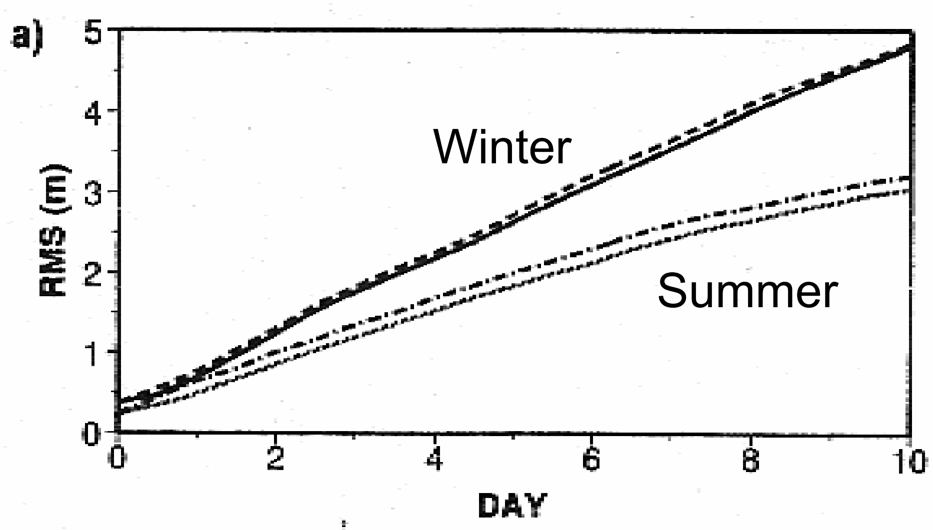
IMPERFECT MODELS – 2

CURRENT METHODS

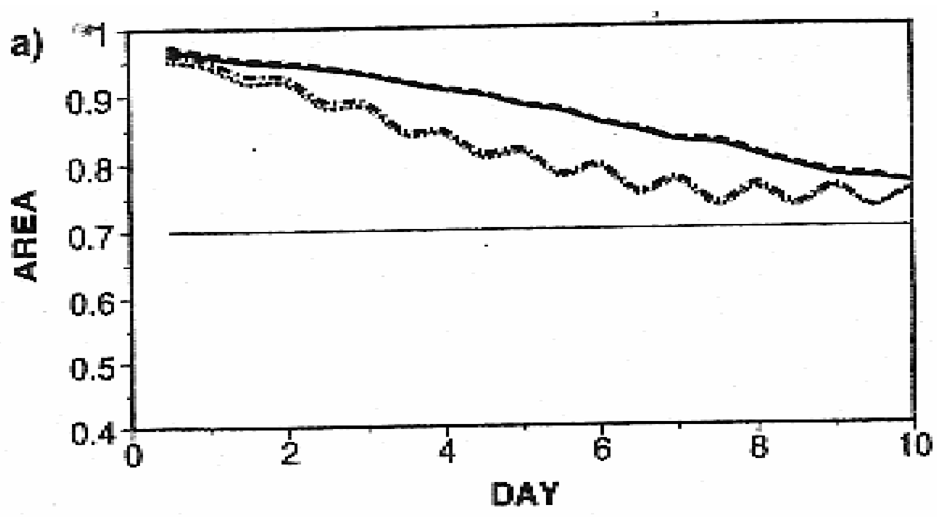
1) Change structure of model (eg, use different convective schemes, etc, MSC)
2) **Add stochastic noise (eg, perturb diabatic forcing, ECMWF)**
   - Modest increase in perturbation growth for tropics
   - Some improvement in ROC skill for precip, for tropics

850 hPa Temp, NH

Spread



ROC Area



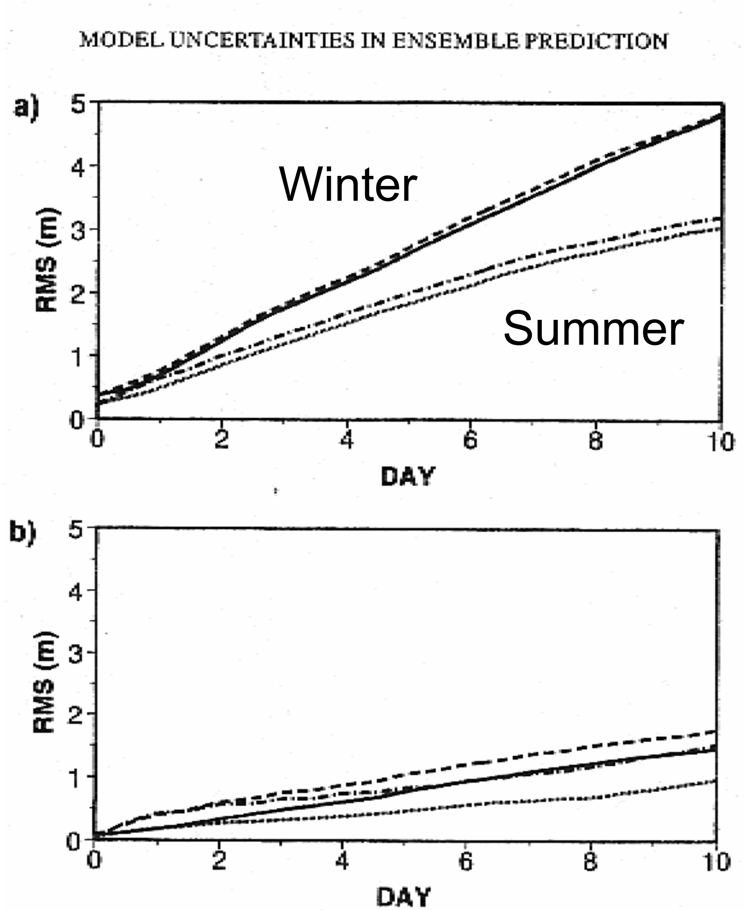
Buizza

Oper vs. Stochastic perturbations

850 hPa Temp

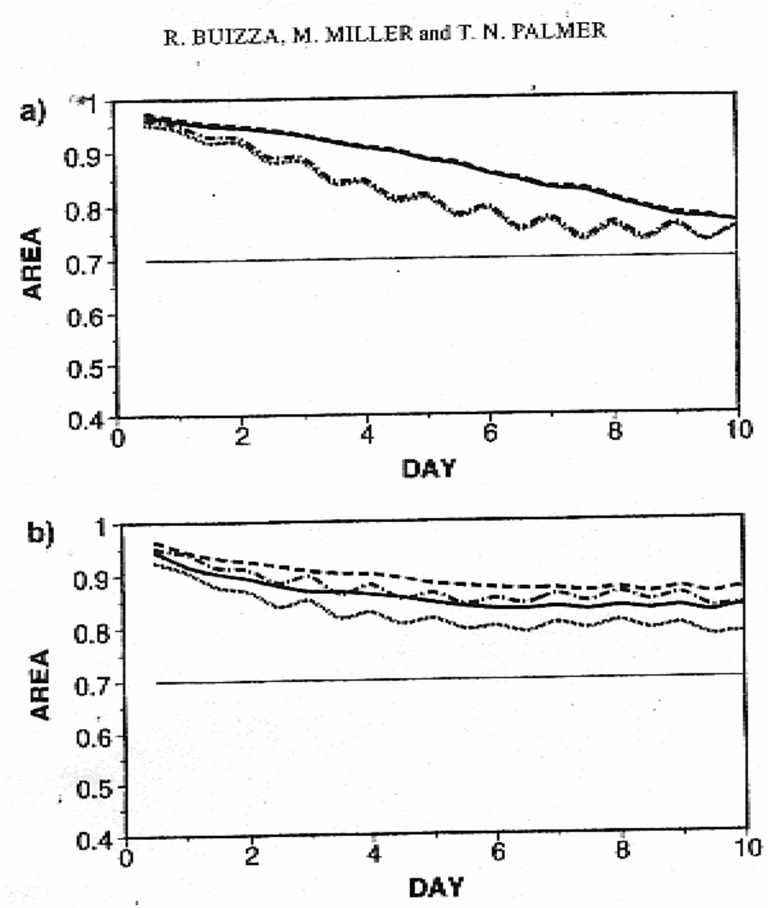
Spread

ROC Area



NH

Tropics



Buizza

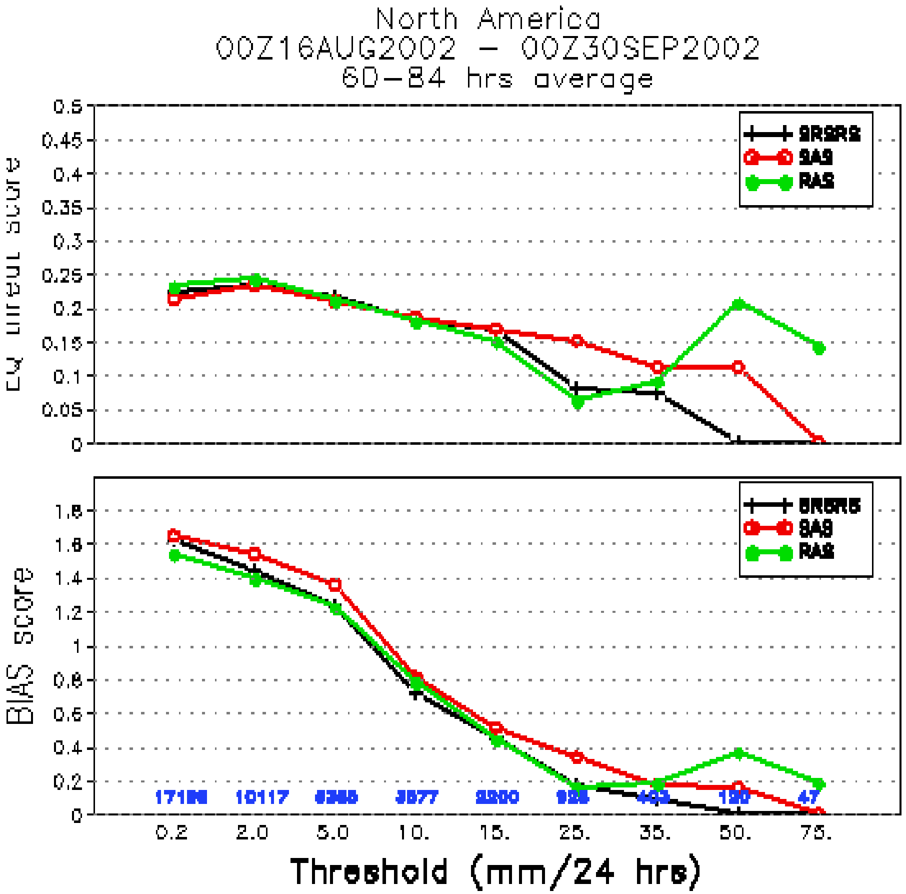
Oper vs. Stochastic perturbations

RESULTS FROM COMBINED USE OF RAS & SAS

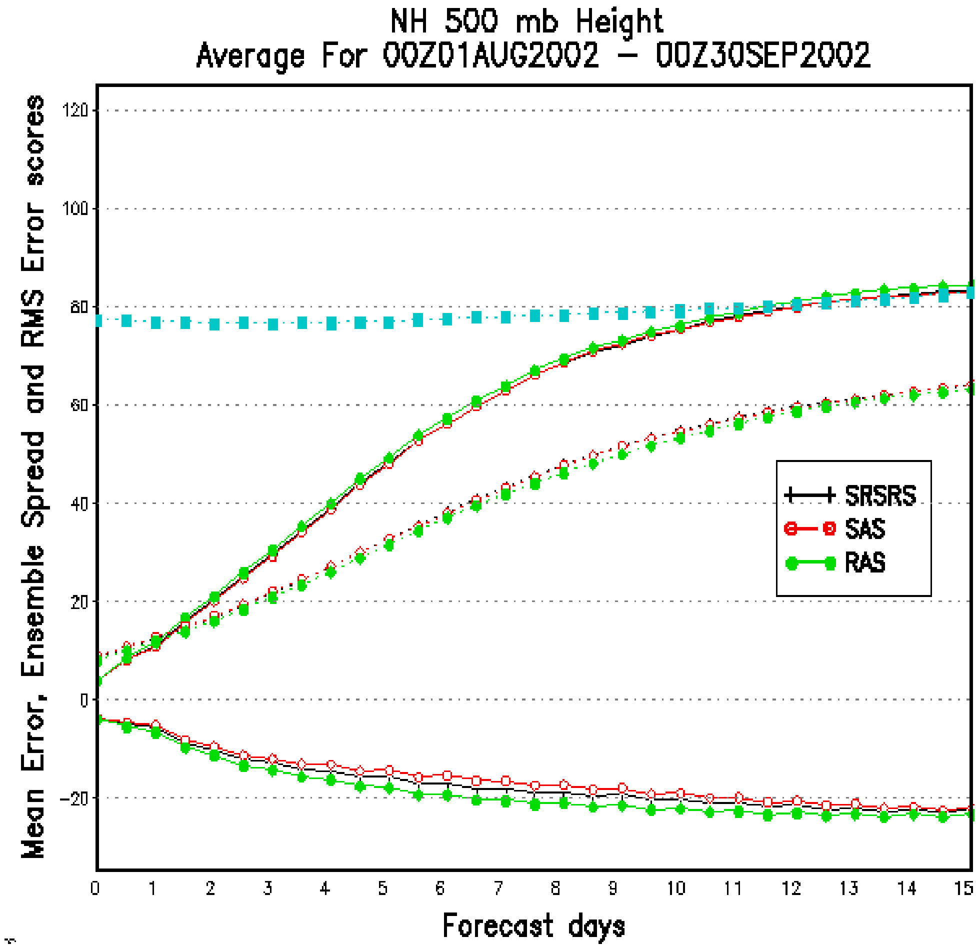
NO POSITIVE EFFECT ON PRECIP OR HEIGHT SCORES

D. Hou

Precipitation Forecast Scores Day 3
SAS, RAS, & Combination



500 hPa height RMS error, NH extratr.
SAS, RAS, & Combination

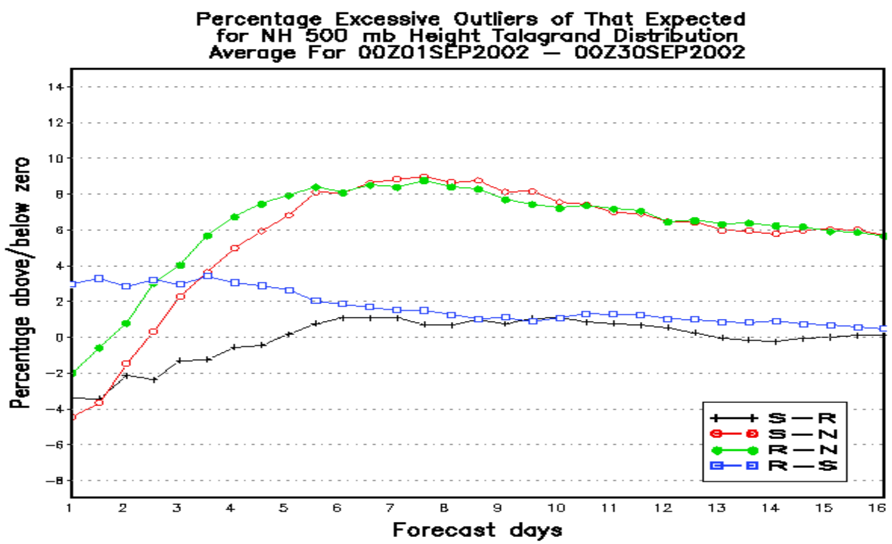


RESULTS FROM COMBINED USE OF RAS & SAS

CONVECTIVE SCHEME DOES NOT SEEM TO HAVE PROFOUND INFLUENCE ON FORECASTS EXCEPT PRECIP

Rank histogram comparing distributions of sub-ensembles relative to each other

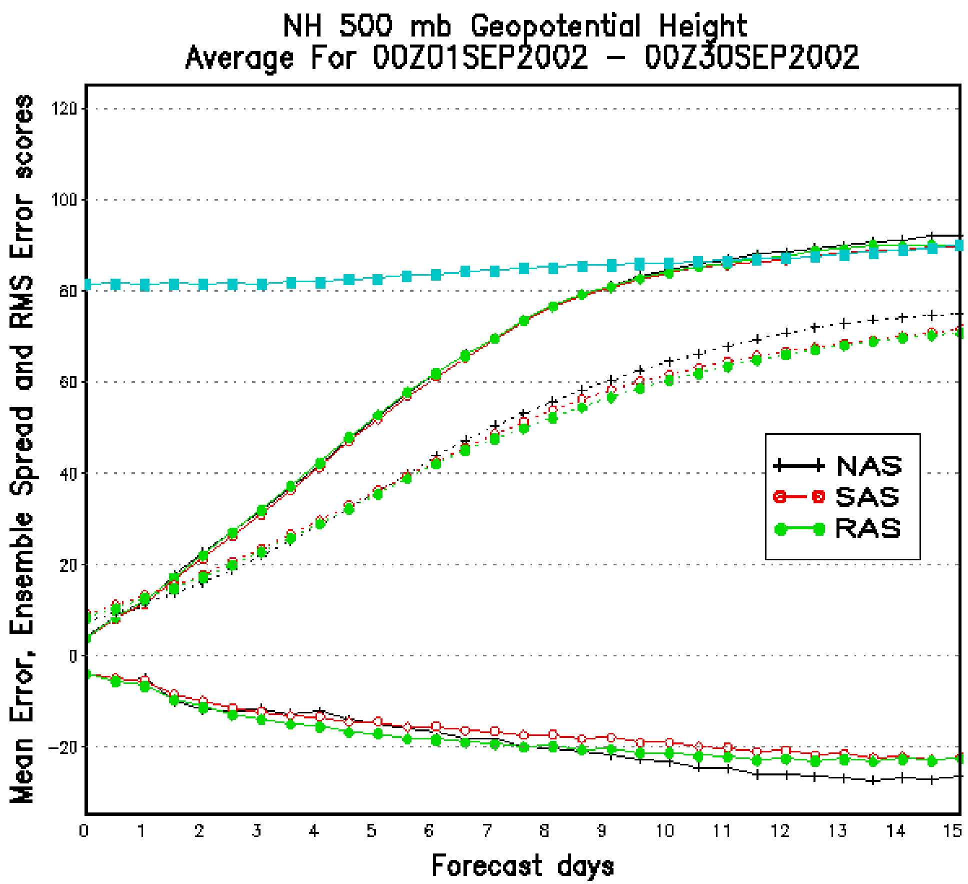
AFTER BIAS CORRECTION, SAS & RAS SUB-ENSEMBLES COVER SAME SUBSPACE



D. Hou

500 hPa height NH extratrop. RMS error for RAS, SAS, and NAS (no convection)

NO DIFFERENCE WHETHER CONVECTIVE SCHEME IS USED OR NOT

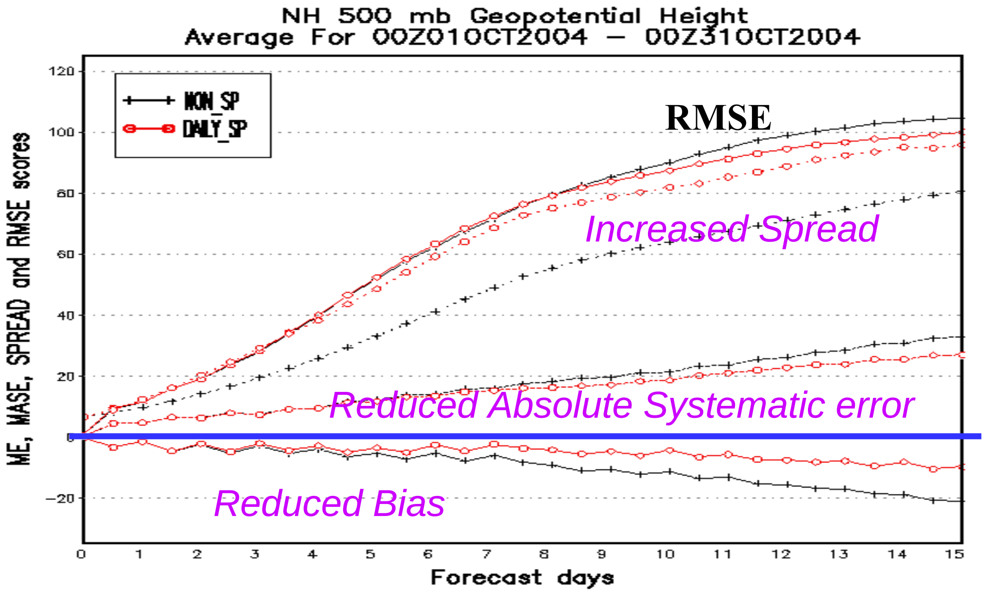


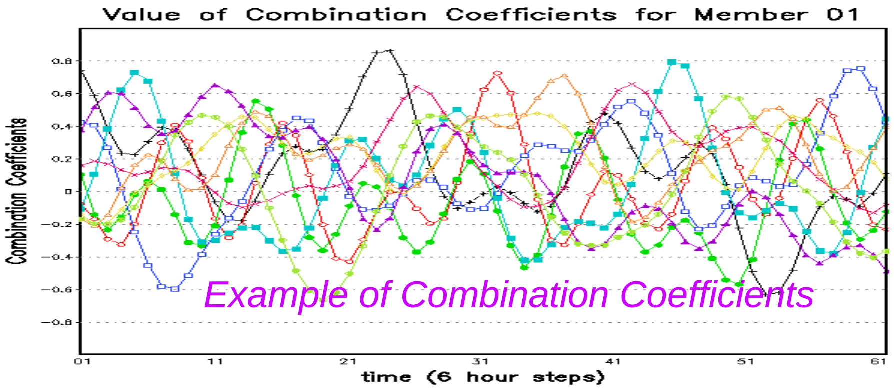
REPRESENTING MODEL RELATED UNCERTAINTY
A STOCHASTIC PERTURBATION (SP) SCHEME

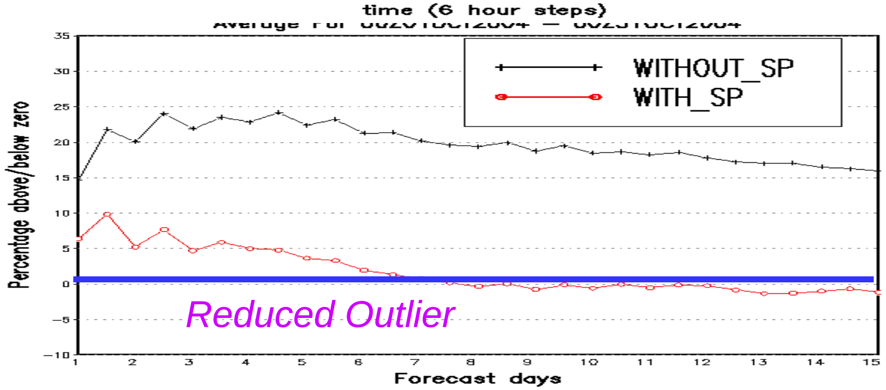
General Approach: Adding a stochastic forcing term in to the tendencies of the model equations.
Strategy: Generate the S terms from (random) linear combinations of the conventional perturbation tendencies.

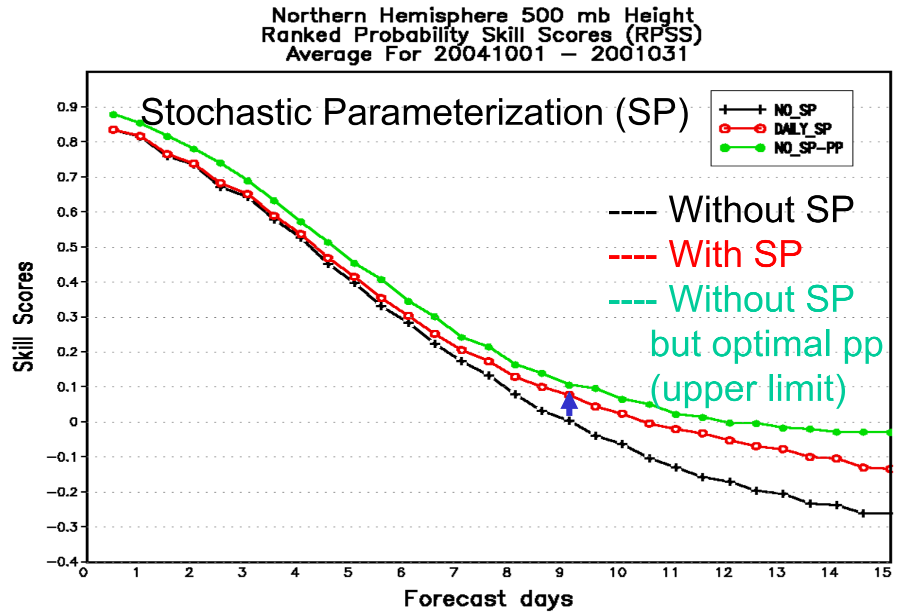
Desired Properties

1. Forcing applied to all variables
2. Approximately balanced
3. Smooth variation in space and time
4. Flow dependent
5. Quasi-orthogonal









STOCHASTIC PERTURBATIONS

AREA OF ACTIVE RESEARCH

- ECMWF operational (Buizza et al, 1999), A random numbe (sampled from a uniform distribution) multiplied to the parameterized tendency
- ECMWF research (Shutts and Palmer, 2004), Cellular Automaton Stochastic Backscatterused to determine the perterbation
- Simple Model Experiment (Peres-Munuzuri, 2003), multiplicative and additive stochastic forcing

NCEP METHOD UNDER TESTING

- Addition of flow-dependent perturbations to tendencies in course of integration

DETAILS – Add to each perturbed member:

- Difference between single high & low-res forecasts (after scaling and filtering)
- Perturbation based on the differences among the ensemble members at previous step in integration
    - Use global or localized perturbation approach
    - Random or guided selection of members (e.g., use difference between most similar members)

REPRESENTING MODEL RELATED UNCERTAINTY
A STOCHASTIC PERTURBATION SCHEME

General Approach: Adding a stochastic forcing term in to the tendencies of the model equations.

Assumption: The perturbations (difference between ensemble members and the control) in the conventional tendencies provide a sample of realizations of the additional stochastic forcing S.

Strategy: Generate the S terms from (random) linear combinations of the conventional perturbation tendencies.

Desired Properties

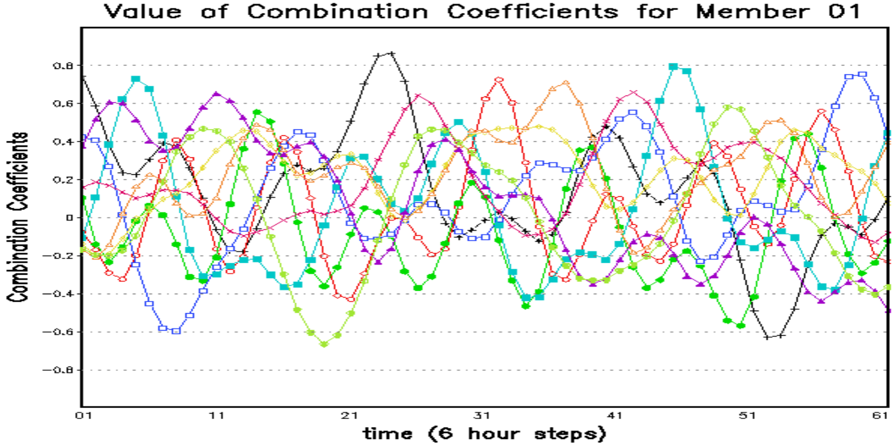
1. Forcing applied to all variables
2. Approximately balanced
3. Smooth variation in space and time
4. Flow dependent
5. Quasi-orthogonal

Expected Results

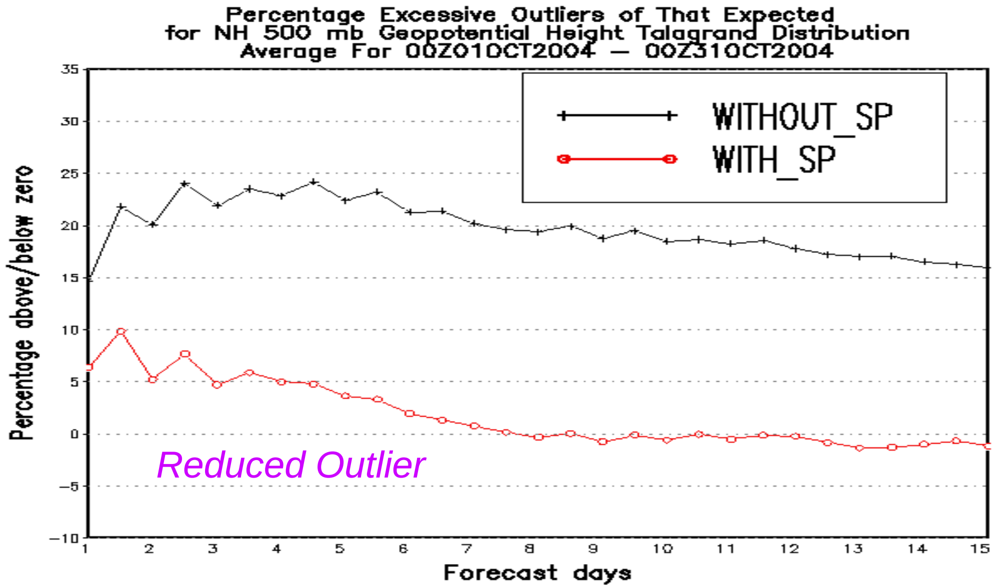
Increased spread

Reduced systematic error

Improved probabilistic forecast



Example of Combination Coefficients



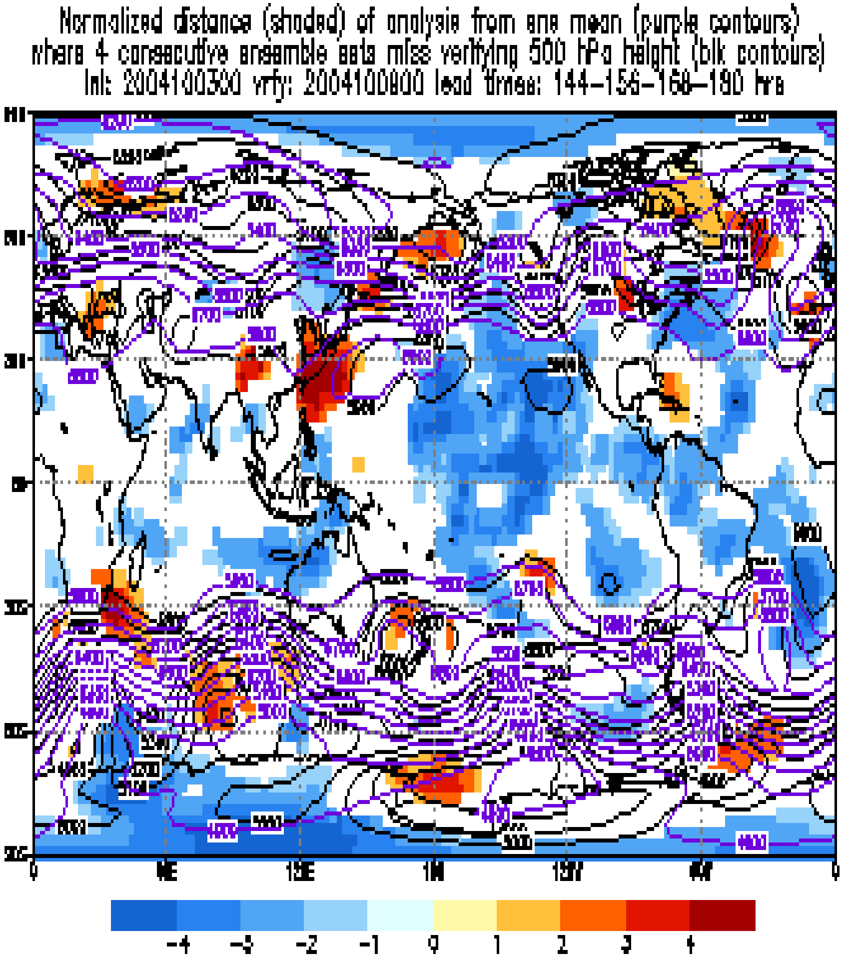
Outliers: H500, day 6 forecast, 20041002

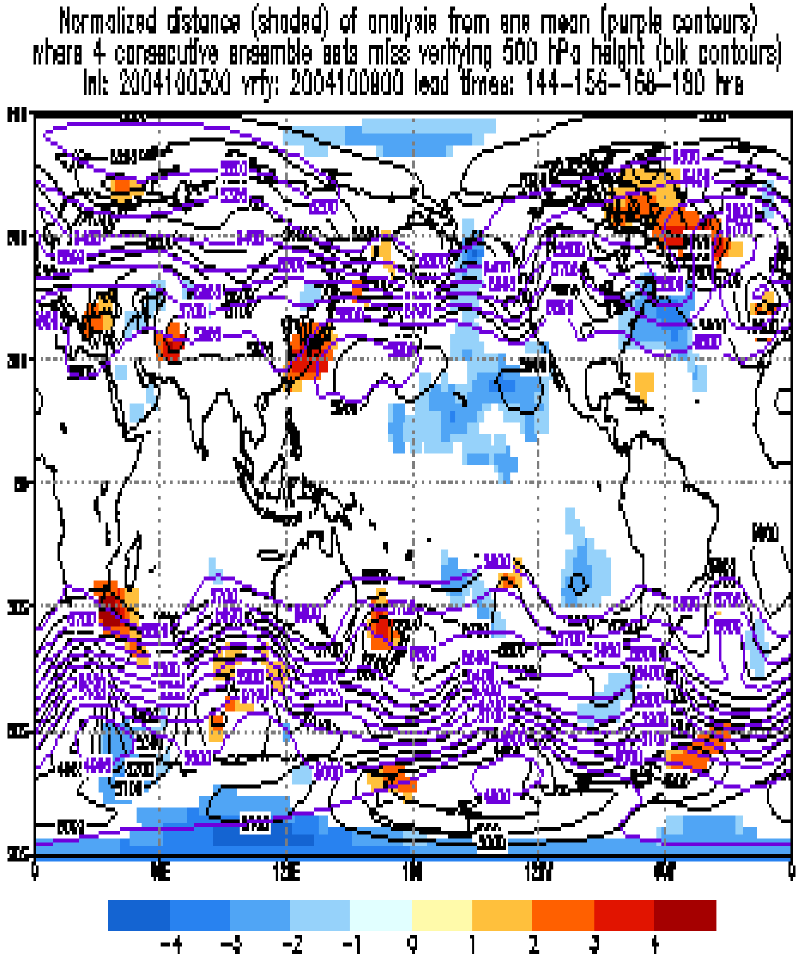
Without SP

large number of outliers with negative and positive forecast bias

With SP

the number of outliers is significantly reduced



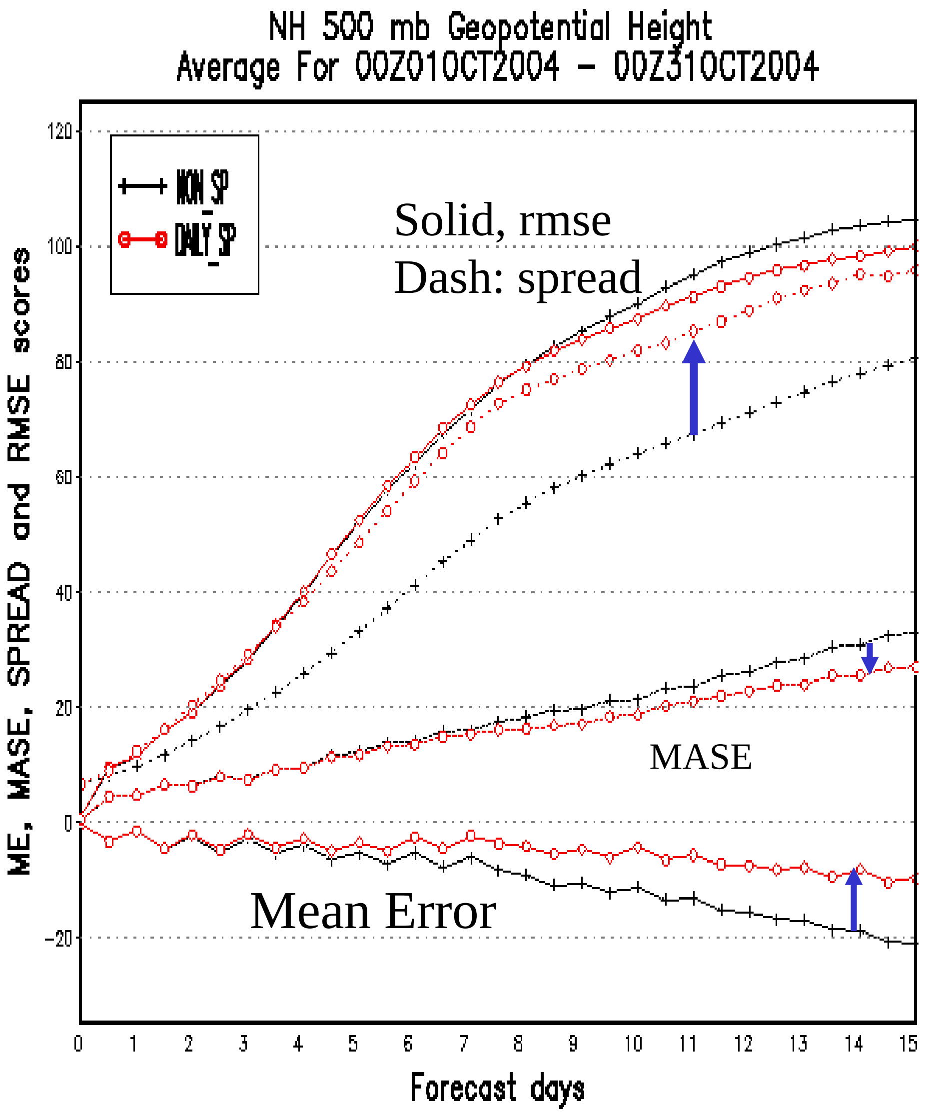


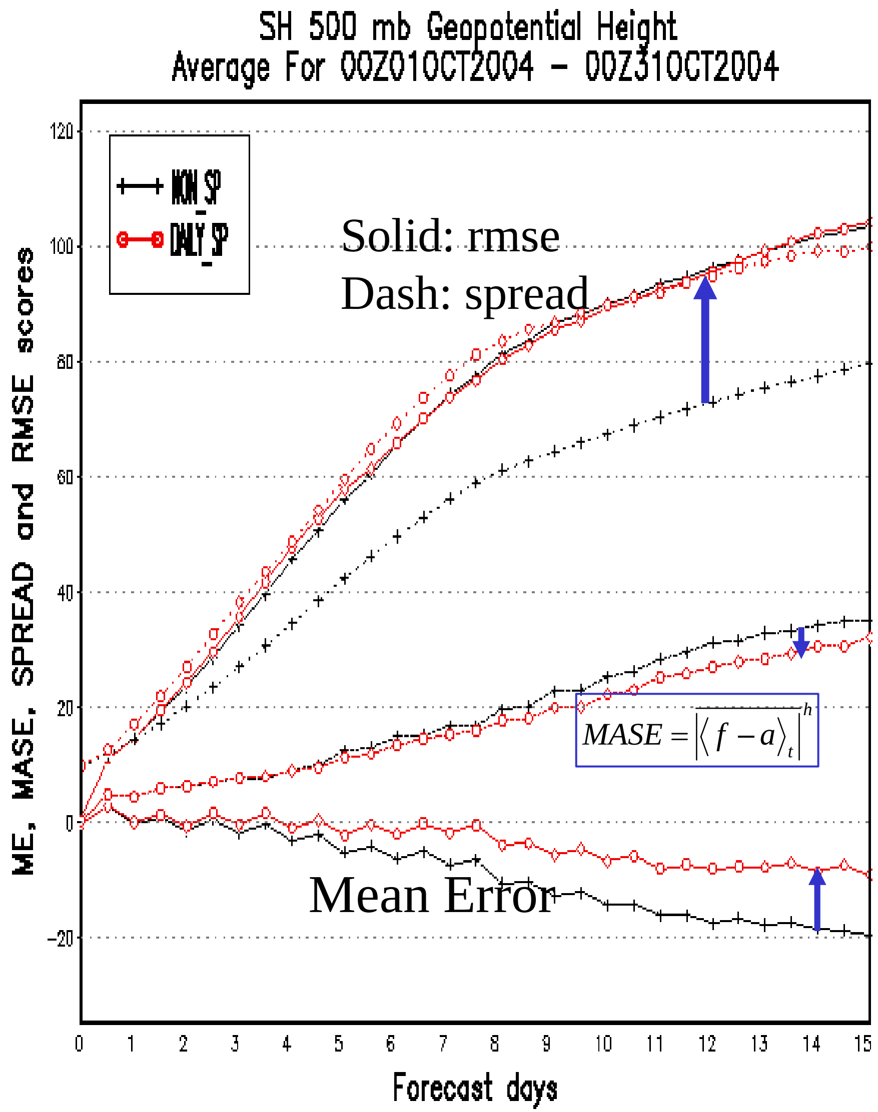
Statistics: Ensemble Spread and Error of Ensemble Mean

Increased Spread, Reduced Mean Error (ME)

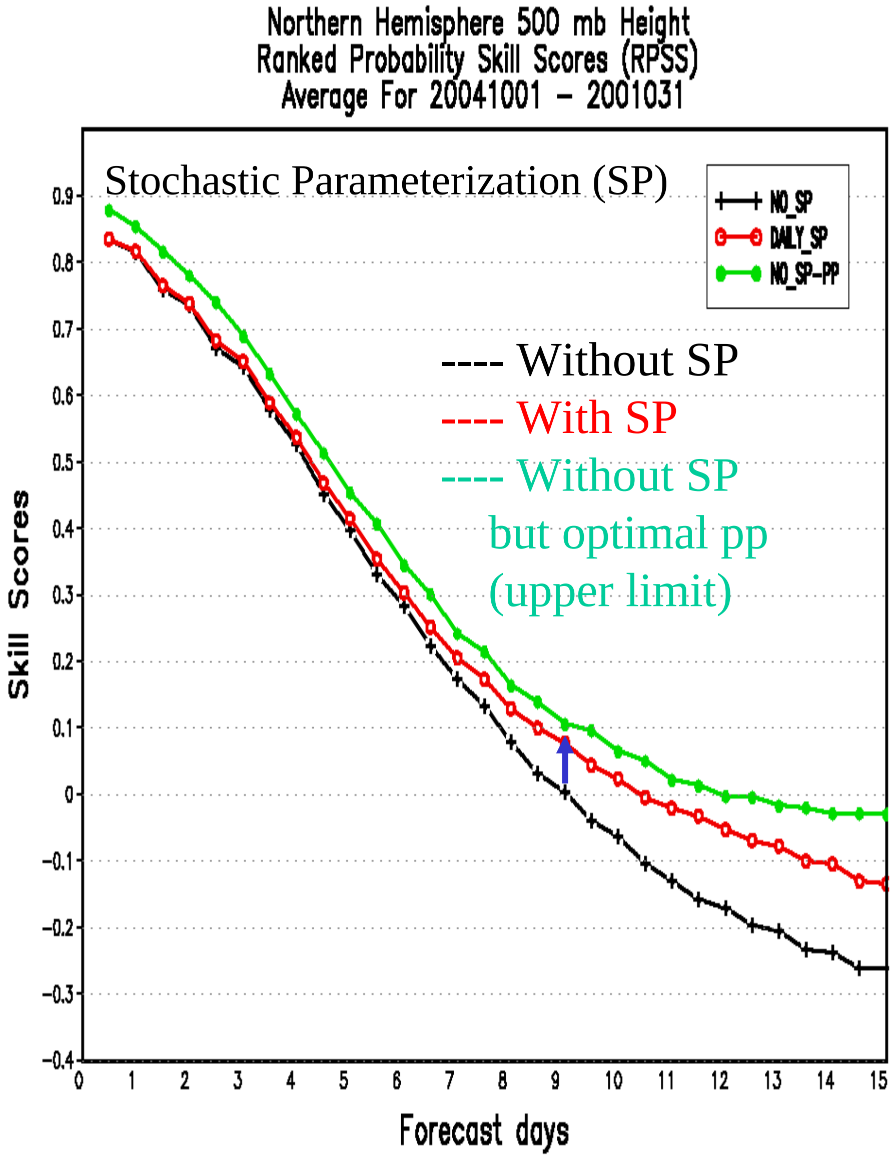
Reduced Mean Absolute Systematic Error (MASE)

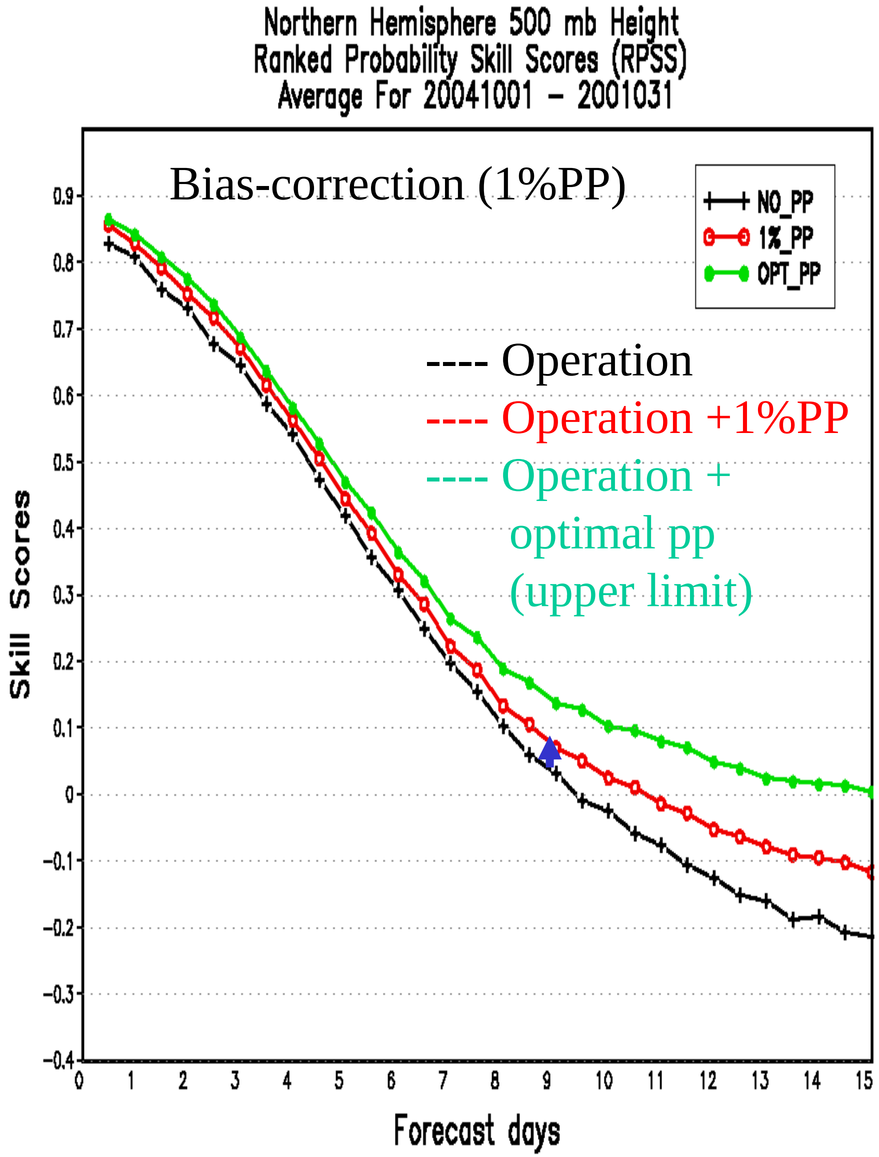
----- Without SP ------- With SP





Comparison with Post-Processing (PP)
RPSS: Improved in both cases (SP and PP)
SP is more effective in week 2 forecast





SAMPLING FORECAST ERRORS =

REPRESENTING ERRORS DUE TO USE OF

IMPERFECT MODELS – 3

CURRENT METHODS

1) Change structure of model (eg, use different convective schemes, etc, MSC)
   - Model version fixed, whereas model error *varies in time*
   - Random/stochastic errors not addressed
   - Difficult to maintain
2) Add stochastic noise (eg, perturb diabatic forcing, ECMWF)
   - Small scales perturbed
   - If otherwise same model used, larger scale biases may not be addressed

Do they work? Advantages of various approaches need to be carefully assessed

- Are flow dependent variations in uncertainty captured?
- Can statistical post-processing replicate use of various methods?

NEED NEW

- *MORE COMPREHENSIVE AND*
- *THEORETICALLY APPEALING*

APPROACH

NEW APPROACH TO NWP MODELING –
REPRESENTING MODEL RELATED UNCERTAINTY

MODEL ERRORS ARE DUE TO:

- Truncation in spatial/temporal resolution –
  - Need to represent stochastic effect of unresolved scales
    - Add parameterized random noise
- Truncation in physical processes resolved
  - Need to represent uncertainty due to choice of parameterization schemes
    - Vary parameterization schemes / parameter values

MODEL ERRORS ARE PART OF LIFE, WILL NEVER GO AWAY

IN ENSEMBLE ERA,

NWP MODELING PARADIGM NEEDS TO CHANGE

	OLD	NEW
GOAL	1^{st} Moment	Probability distribution
MEASURE	RMS error	Probabilistic scores
VARIANCE	Ignored / reduced	Emphasized
NWP MODEL	Search for best configuration	Represent uncertainty

NEW APPROACH TO NWP MODELING –
REPRESENTING MODEL RELATED UNCERTAINTY

IT IS NOT ENOUGH TO PROVIDE SINGLE (BEST) MODEL FORECAST

JOINT EFFORT NEEDED BETWEEN MODELING & ENSEMBLE COMMUNITY

FOR OPTIMAL ENSEMBLE PERFORMANCE,

MODELS NEED TO REALISTICALLY REPRESENT ALL MODEL-RELATED

Resolution (time and space truncation)

Parameterization-type (unresolved physics)

UNCERTAINTY AT THEIR SOURCE -

Like in case of initial condition-related uncertainty

FOR MODEL IMPROVEMENTS,

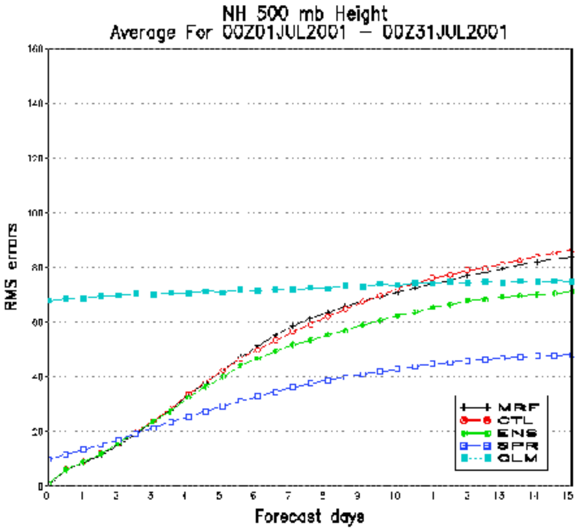
ENSEMBLE OFFERS TOOL TO SEPARATE INITIAL & MODEL ERRORS

Case dependent errors can be captured and corrected

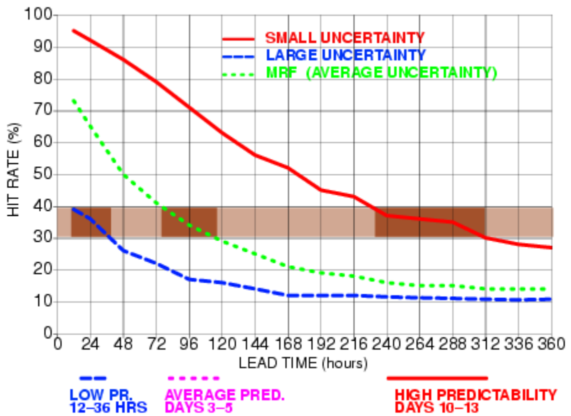
WILL NEW APPROACH ADD VALUE?

WILL IT ENHANCE RESOLUTION OF PROBABILISTIC FCSTS?

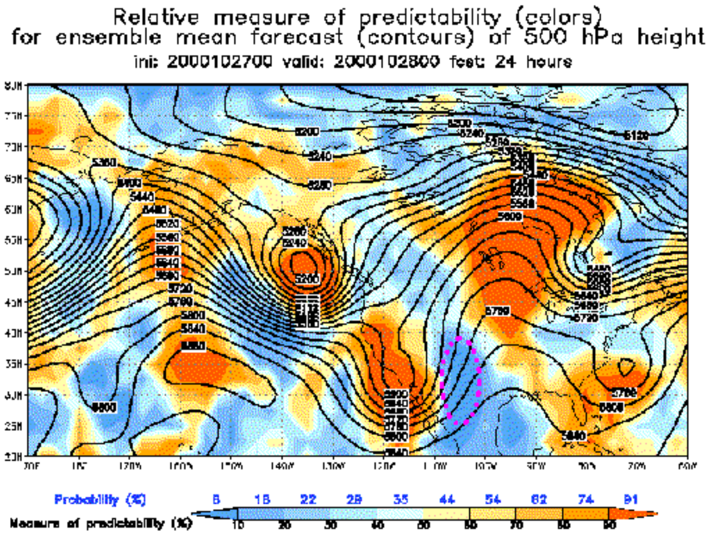
WILL IT GIVE CASE-DEPENDENT ESTIMATES (INSTEAD OF AVERAGE STATISTICAL MEASURE) OF MODEL-RELATED UNCERTAINTY?

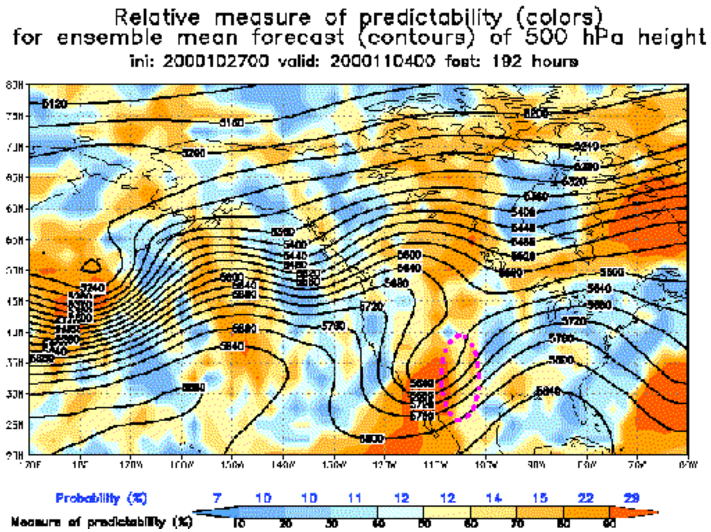


SEPARATING HIGH VS. LOW UNCERTAINTY FCSTS



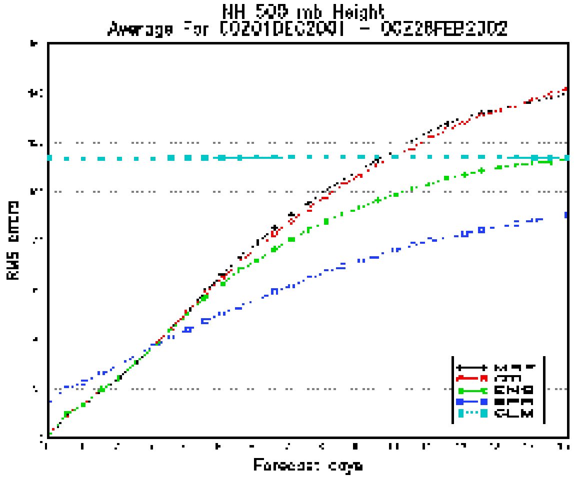
UNCERTAINTY OF FCSTS CAN BE QUANTIFIED IN ADVANCE



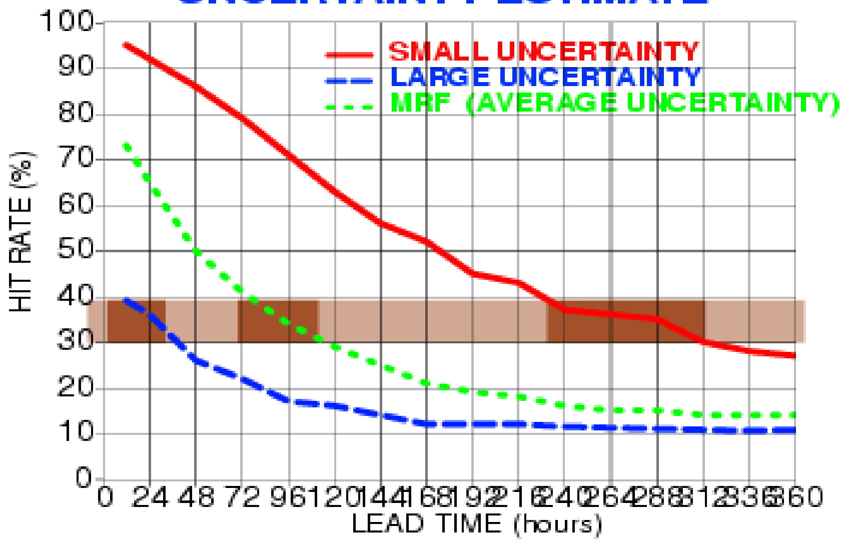


ADVANTAGES OF USING ENSEMBLE (VS. CONTROL) FCSTS

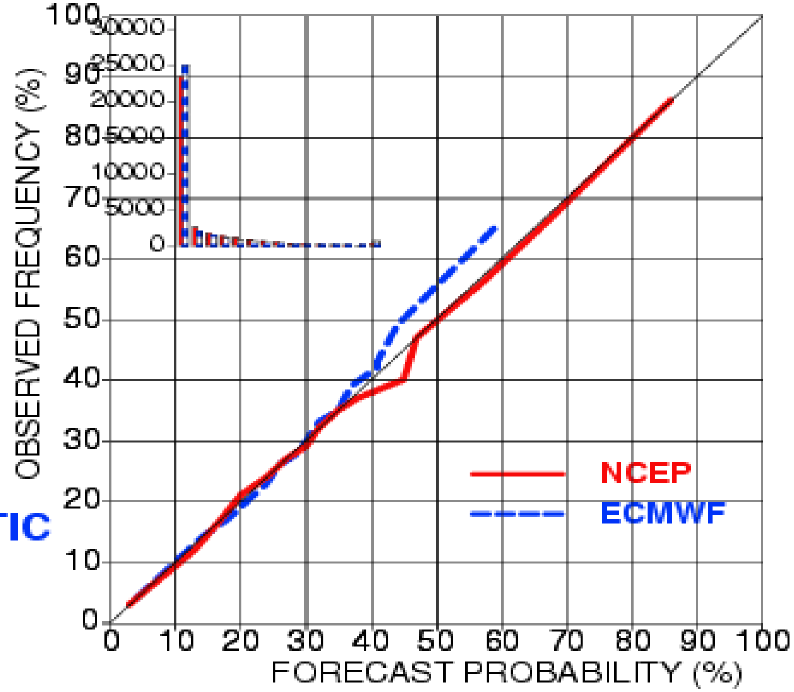
1) IMPROVED EXPECTED VALUE FORECAST



2) CASE DEPENDENT UNCERTAINTY ESTIMATE



3) DETAILED PROBABILISTIC FORECAST



OUTLINE / SUMMARY

- TRADITIONAL NWP APPROACH
  - REDUCE FORECAST UNCERTAINTY
  - IGNORE REMAINING ERRORS
    - Problem for users

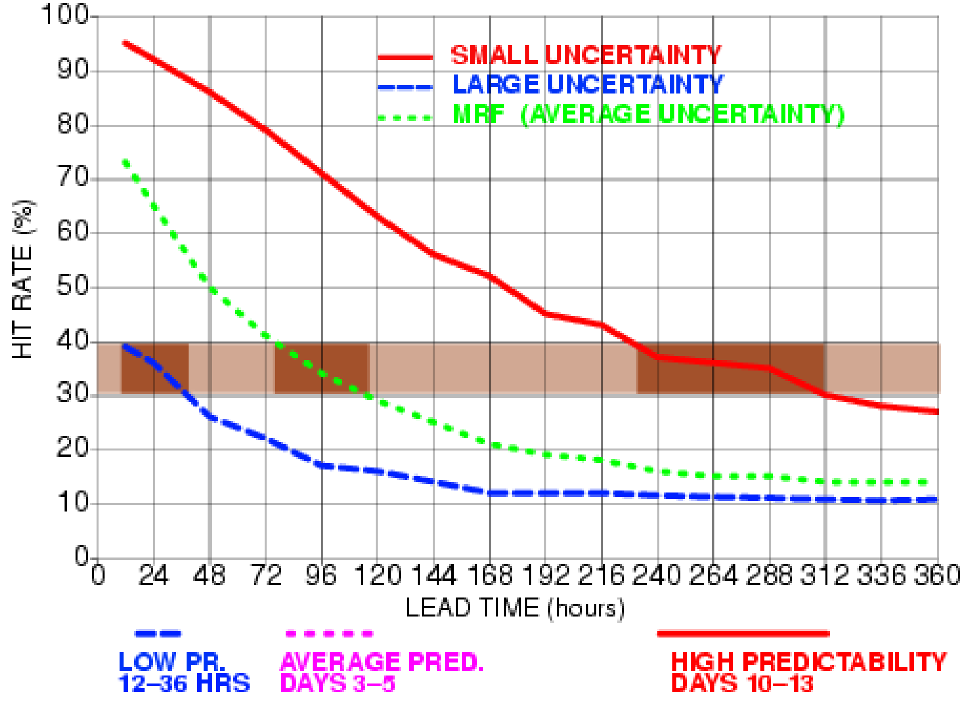
- SOURCES OF FORECAST ERRORS
  - INITIAL CONDITION
  - NUMERICAL MODEL

- ESTIMATING AND SAMPLING FORECAST ERRORS
  - INITIAL CONDITION
    - Breeding technique / ET
  - MODEL ERRORS
    - No solid scientific basis, open research

- POTENTIAL VALUE OF ENSEMBLE APPROACH
  - IMPROVED SINGLE VALUE ESTIMATE
  - CASE DEPENDENT ESTIMATE OF UNCERTAINTY
  - FULL PROBABILITY DISTRIBUTION / TRAJECTORIES

BACKGROUND

SEPARATING HIGH VS. LOW UNCERTAINTY FCSTS



THE ***UNCERTAINTY OF FCSTS*** *CAN BE* ***QUANTIFIED IN ADVANCE***

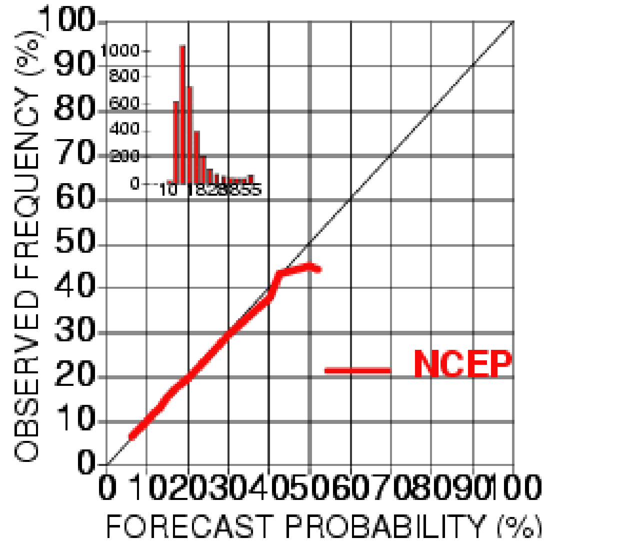
HIT RATES FOR 1–DAY FCSTS

CAN BE ***AS LOW AS 36%****, OR* ***AS HIGH AS 92%***

10–15% OF THE TIME A 12–DAY FCST CAN BE AS GOOD, OR A 1–DAY FCST CAN BE AS POOR AS AN AVERAGE 4–DAY FCAST

1–2% OF ALL DAYS THE 12–DAY FCST CAN BE MADE WITH MORE CONFIDENCE THAN THE 1–DAY FCST

AVERAGE HIT RATE FOR EXTENDED–RANGE FCSTS IS LOW –
VALUE IS IN KNOWING WHEN FCST IS RELIABLE



Reliability diagram for 240–hour lead time 500 hPa height NH extratropics forecasts between March and May 1997. Forecast probabilities are based on how many ensemble members fell in any of 10 climatologically equally likely bins at each gridpoint, and are calibrated using verification statistics from the winter of 1995–96. Insert in upper left corner shows in how many events a particular forecast probability was used for the most likely bin (ensemble mode).

ENSEMBLES: WHEN?

- Single forecast approach favored when
  - ***Case-dependent variations*** are weak in
    - Level of linear error growth at short lead times
    - Pdf evolution at short lead times (ie, quasi-linear behaviour)
    - Model-related error behaviour (at any lead time)
  - Aggregate bias-correction algorithms adequate
- Use ensembles otherwise
  - Review criteria above for each application
  - Bias-correct both single value & ensemble forecasts (ie, pdf)
    - Decide on forecast configuration based on results
- "Generic" configuration
  - Higher resolution control for short lead time if beneficial
  - Lower resolution ensemble out to longer lead times
    - Benefits from combining hi-re control & lo-res ensemble at shorter leads?
- Considerations
  - Integrations must resolve phenomena of interest
    - Unless sophisticated statistical down-scaling techniques can be developed

PROPAGATING FORECAST UNCERTAINTY

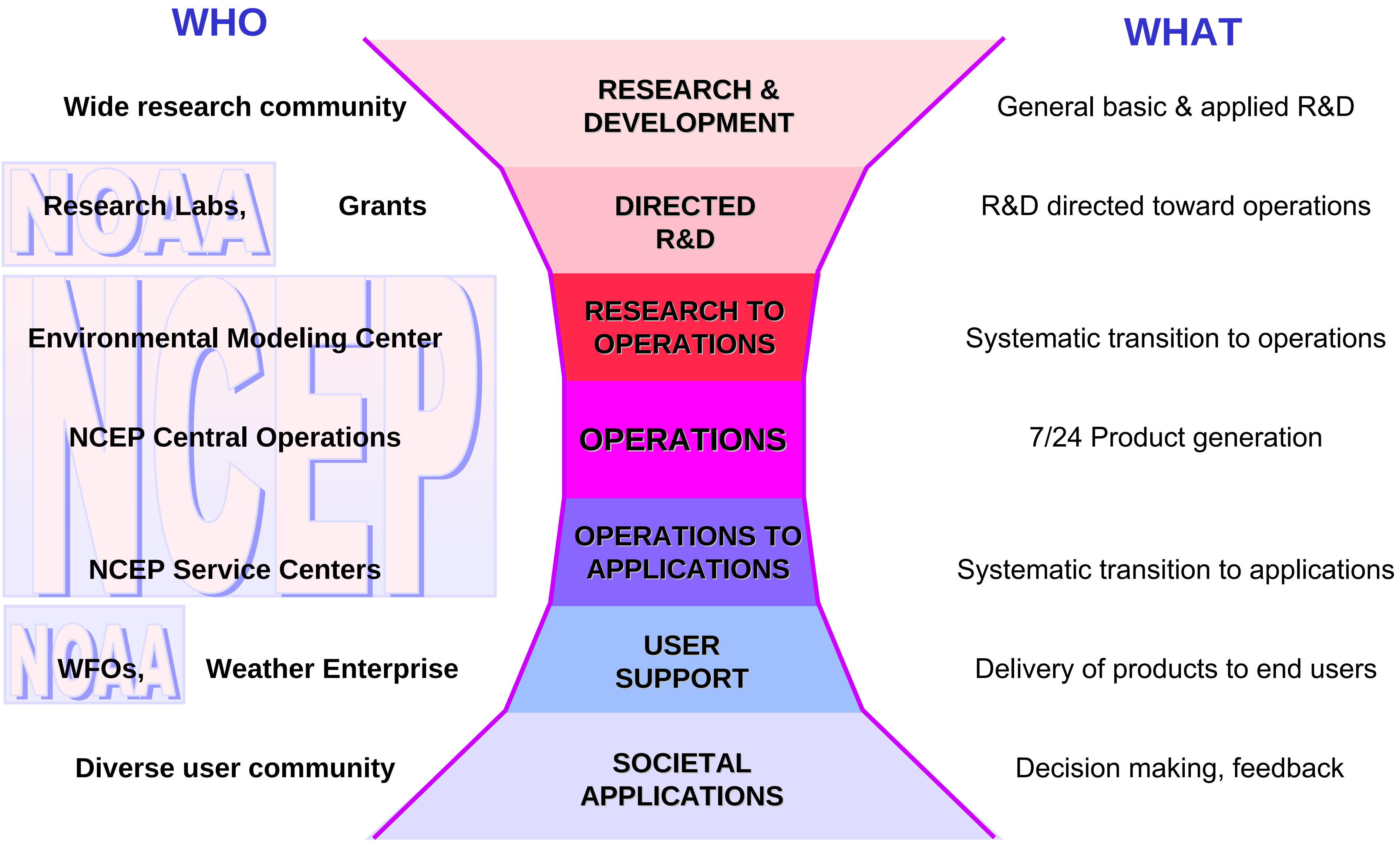
OLD PARADIGM: Reduce Uncertainty	***FORECAST PROCESS***	**NEW PARADIGM:** Reduce & Assess Uncertainty
Misconstrued determinism	NATURE	Critical sensitivity to initial conditions - Chaos
Reduce obs. uncertainty	OBSERVING SYSTEM	Quantify obs. uncertainty
Estimate expected value	DATA ASSIMILATION	Estimate distribution
Reduce model errors	NWP MODELING	Reduce & represent model errors
Ad hoc opportunities	**ENSEMBLE FORECASTING**	Systematic approach
Reduce systematic error	STATISTICAL POST-PROCESSING	Calibrate uncertainty
Single value	BASIC PRODUCTS	Distributional characteristics
Yes or No forecasts tailored for decisions	USER SUPPORT SYSTEMS	Incorporate forecast uncertainty info
Limited forecast info - Restricted usage	SOCIETY	All forecast info – Optimal user decisions

Single value

Distribution

Ensemble Forecasting:
Central role – bringing the pieces together

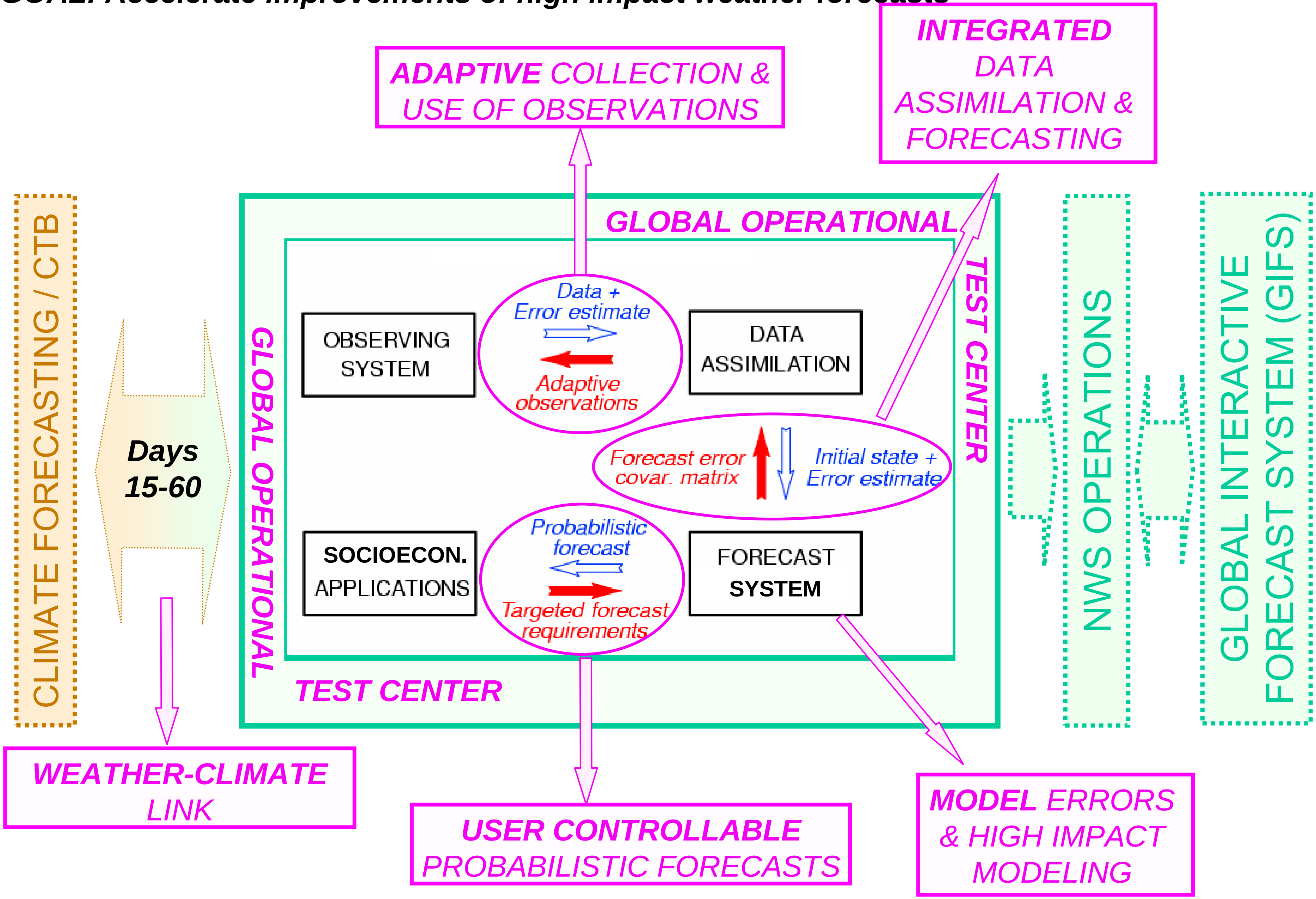
RESEARCH TO OPERATIONS TO APPLICATIONS FUNNEL



ENSEMBLES AND THE RESEARCH COMMUNITY

LINKED THROUGH THORPEX – MAJOR INTERNATIONAL RESEARCH PROGRAM

GOAL: Accelerate improvements of high impact weather forecasts



ENSEMBLES AND NOAA SERVICES

- NWS requirements must be redefined
  - NWS operations is strictly requirement driven
    - Culture must change to support evolution in operations

- New emphasis on high impact events
  - W&W Goal & EMP Sub-Goal involvement
- High Impact Events Theme
  - Adaptive and event driven
  - Integrated across the spectrum of services
  - Probabilistic approach
  - Enhanced automated guidance
  - New role for forecasters
  - Environmental Information Repository

- "Establish comprehensive suite of ensemble forecast systems ("forecast engine") that will facilitate the generation of automated forecast guidance products in the framework of the new NOAA CONOPS as the basis ("forecast engine") for NOAA operations regarding high impact events:
  - New automated "forecast engine that adapts to high impact events
    - Adaptive observations
    - Adaptive ensemble suite
    - Statistical post-processing

CONSIDERATIONS FOR OPERATIONAL IMPLEMENTATIONS

- Performance
  - Offline research, parallel development, pre-implementation testing
    - **User relevant verification statistics** (ie, bias corrected & downscaled forecasts)

- Economy
  - Operations is narrowest point in Research-Operations-Applications funnel
    - Lots of research/development, **one system in operations**
    - **Computational efficiency**

- Maintenance
  - Minimize work needed for transfer (R2O, O2A, from machine to machine, etc)
    - **Unified approaches** preferred if performance not sacrificed

- Interconnectedness
  - Each piece of operations intimately connected with rest of system
    - **Incremental improvements** to existing system OR
    - Very careful **long-term planning** for major upgrades

ENSEMBLE DEVELOPMENT CONSIDERATIONS

- Common scientific principles - Chaos affects all spatial/temporal scales
  - Quantify all forecast uncertainty - Inseparable from forecasting in general
    - Links with observing system, data assimilation, numerical modeling, user applications
  - Represent all forecast uncertainty at their source - Otherwise poor reliability
    - Only chance to propagate true uncertainty through forecast process
- Unified approach
  - Common techniques across applications wherever appropriate / possible
- Ensemble team members
  - Work in implementation teams, coordinated with rest of EMC & NCO
  - Interact with broader research and user communities

COMPONENT		Adaptive Observations	Initial Perturbations	Model Perturbations	Statistical Post-Proc.	Product Generation	Verification
FORECAST SYSTEM LINK		*Obs. System Design*	*Data Assimilation*	*Numerical Modeling*			
APPLICATION	PEOPLE	Masutani, Song,	Wei	Hou, Du	Cui, Pena	Zhou, Zhu	Zhu, Zhou, Hou
Coupled	Pena						
Global	Zhu, Wobus						
Regional	Du						
High-Impact							
Ocean wave	Chen						
Sea Ice	Grumbine						
Riverflow/ Land-surface	Hou						