DATA ASSIMILATION AND ENSEMBLE FORECASTING

Zoltan Toth[(1)]

Mozheng Wei[(2)], Dingchen Hou[(3)], and Yuejian Zhu[(1)]

Acknowledgements: Craig Bishop[(4)]

(1) : NCEP/EMC, Washington, US (http://wwwt.emc.ncep.noaa.gov/gmb/ens/index.html)
(2) : UCAR Visiting Scientist, NCEP/EMC, Washington, US
(3): SAIC at NCEP/EMC
(4): NRL

OUTLINE

- GOALS OF DATA ASSIMILATION
- LINKS BETWEEN DA & ENSEMBLE FORECASTING
- DA ISSUES IN ERA OF SATELLITES
- FORECASTING IN A CHAOTIC ENVIRONMENT
- ESTIMATING & SAMPLING INITIAL ERRORS
- ESTIMATING & SAMPLING MODEL RELATED ERRORS

GOAL OF DATA ASSIMILATION

*Provide **smooth/continuous estimate** of 3-D (4-D) state of natural systems*

- **Two distinct applications**
  - ***"Analysis of record"*** – to assess what happened
    - Utmost fidelity to reality is wanted
      - Eliminate influence of systematic model error
      - Diagnostic, climatological, etc applications
      - Success measured as fit to independent, unbiased data

  - ***Initial condition for forecasting –*** to predict what will happen
    - Best forecast is sought
      - No need to match observations if that hurts forecast
        - » Use only data to the extent it is representative in the modeling system
        - » Do not correct for systematic model errors?
      - Success measured in forecast skill (ie, forecast fit to observed data)

- ***Need different DA approaches for the two different applications?***

- ***Will focus on forecast initial condition applications***

LINK BETWEEN DA & ENSEMBLE FORECASTING

- **INITIAL CONDITION**
  - Weighted average of info from 2 sources:
    - Observational data
    - Numerical forecast
  - Weights depend on errors
    - Need uncertainty information
    - ***Link with ensemble forecasting***

- **ENSEMBLE INITIAL PERTURBATIONS:**
  - Must reflect uncertainty in initial condition
    - ***Link with data assimilation***

- **ENSEMBLE FORECASTS**
  - Must reflect forecast uncertainty due to errors in
    - Initial conditions
    - Model formulation

LINK BETWEEN DA & ENSEMBLE FORECASTING - 2

- **WHAT CAN/SHOULD DA DELIVER TO ENSEMBLES?**
  - Uncertainty in initial condition
    - Variance
    - ***Covariance?***

- **WHAT CAN/SHOULD ENSEMBLES DELIVER TO DA?**
  - Uncertainty in background forecast field
    - Variance
    - Covariance

- **HOW DA & EF SHOULD BE CONFIGURED TO WORK SYMBIOTICALLY?**

LINK BETWEEN DA & ENSEMBLE FORECASTING - 3

GOAL

- Provide best possible ensemble forecast
  - Success measured by skill of ensemble forecasts

APPROACH

- Combine DA & EF systems
  - Data assimilation:
    - How to combine info from observations and background forecasts?
  - Ensemble forecasting:
    - How to estimate forecast uncertainty
  - ***What is the role of each system for particular applications?***
  - ***What is the best way to ensure consistency between DA & EF?***
    - *Comments/examples for some applications with current data coverage for atmosphere*

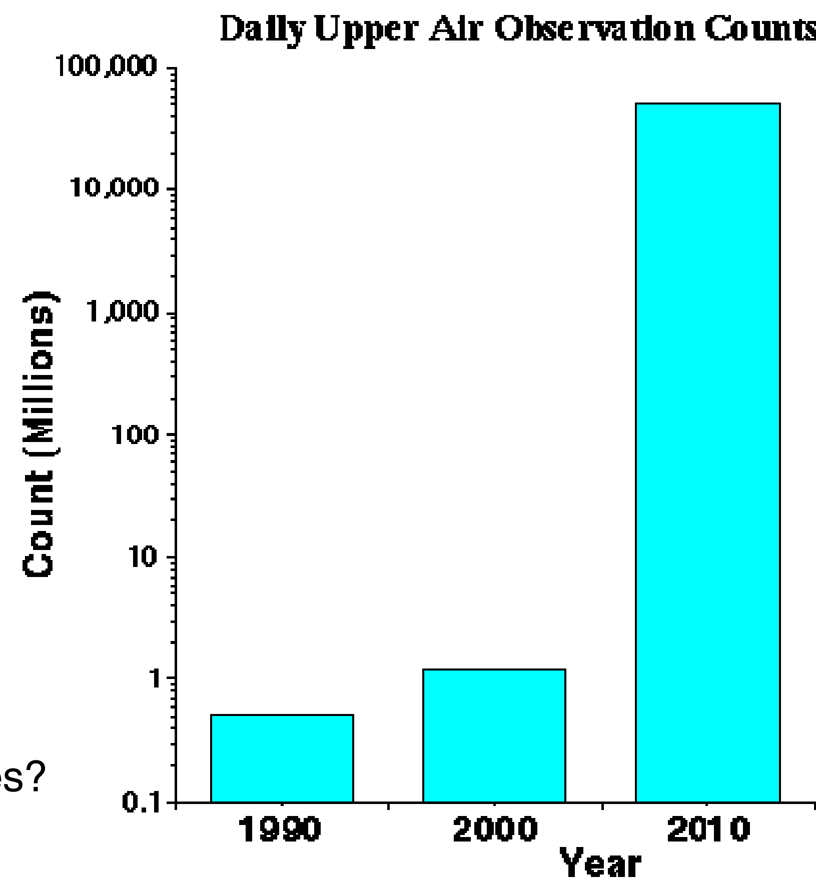
THE ROLE OF DA IN THE ERA OF REMOTE SENSING

Remote sensing provides **high density 3-4D data coverage**

- Number of satellite, radar, etc observations increases exponentially
  - Smooth, quasi-continuous fields
- Some gaps in space/time/variables still remain
- No adequate data on smaller scales?

- **Role of DA schemes diminishes?**
  - More data =>
  - Less need for using forecast information =>
  - Relatively less work for DA
  - Less to be gained now than 20 yrs ago

- **Increased academic/user interest in DA**
  - Still justified
    - Improvements can bring significant gains in forecast skill
    - Challenges remain
      - How to assimilate data on smaller scales?
      - Adaptive "thinning" of data
      - 4DVAR and/or ensemble-based methods?



FORECASTING IN A CHAOTIC ENVIRONMENT

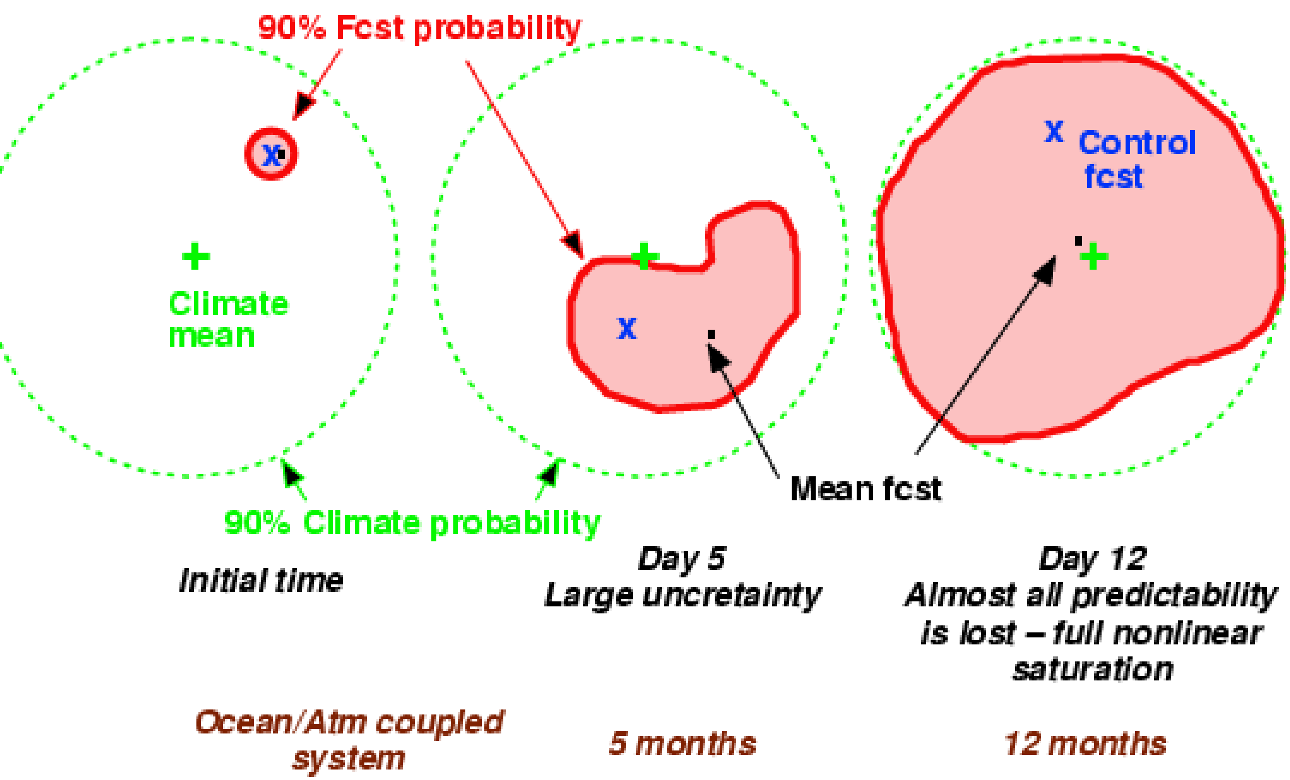
DESCRIBE FORECAST UNCERTAINTY ARISING DUE TO CHAOS

ORIGIN OF FORECAST UNCERTAINTY

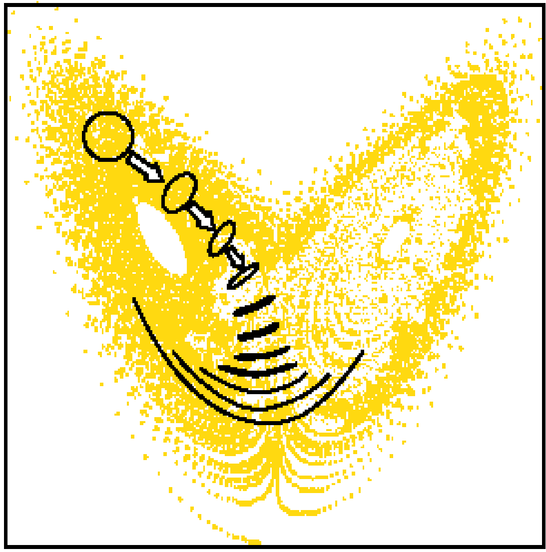
1) The atmosphere is a **deterministic system** *AND* has at least one direction in which **perturbations grow**

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

Chaotic system + Initial error =(Loss of) Predictability



Buizza 2002



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***

- Initialize with probability distribution function (pdf) at analysis time
- Dynamical forecast of pdf based on conservation of probability values
- **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 - 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 1^{st}, 2^{nd}, higher moments)

CAPTURES FLOW DEPENDENT VARIATIONS

IN FORECAST UNCERTAINTY

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; wave-number 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

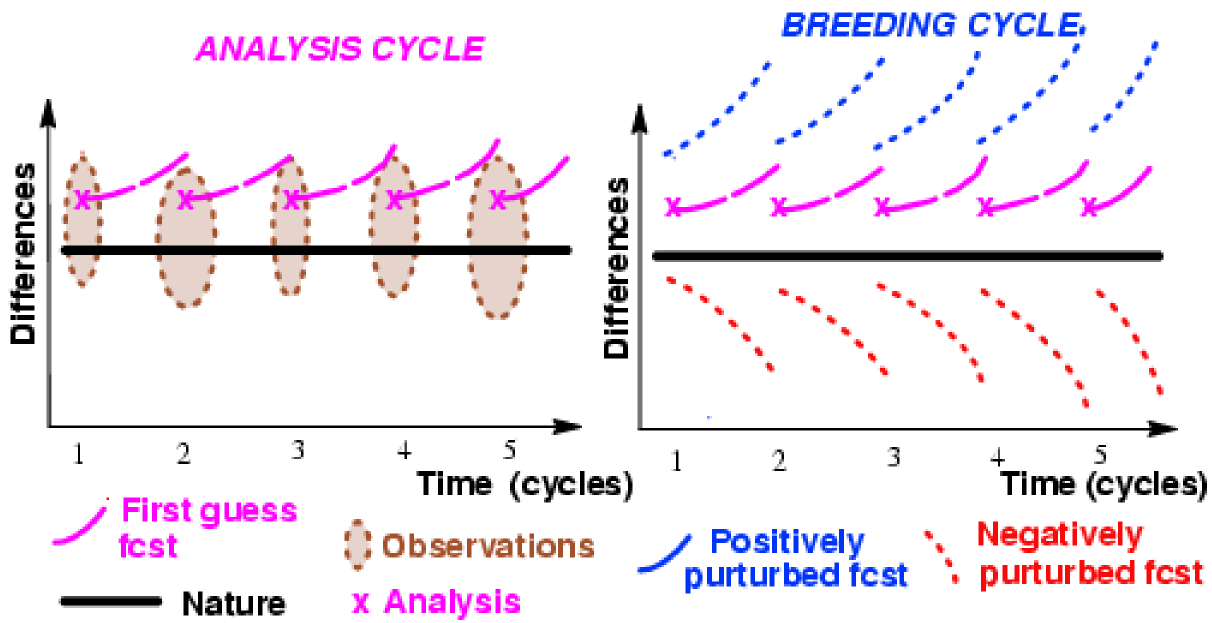
SAMPLING INITIAL CONDITION ERRORS

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

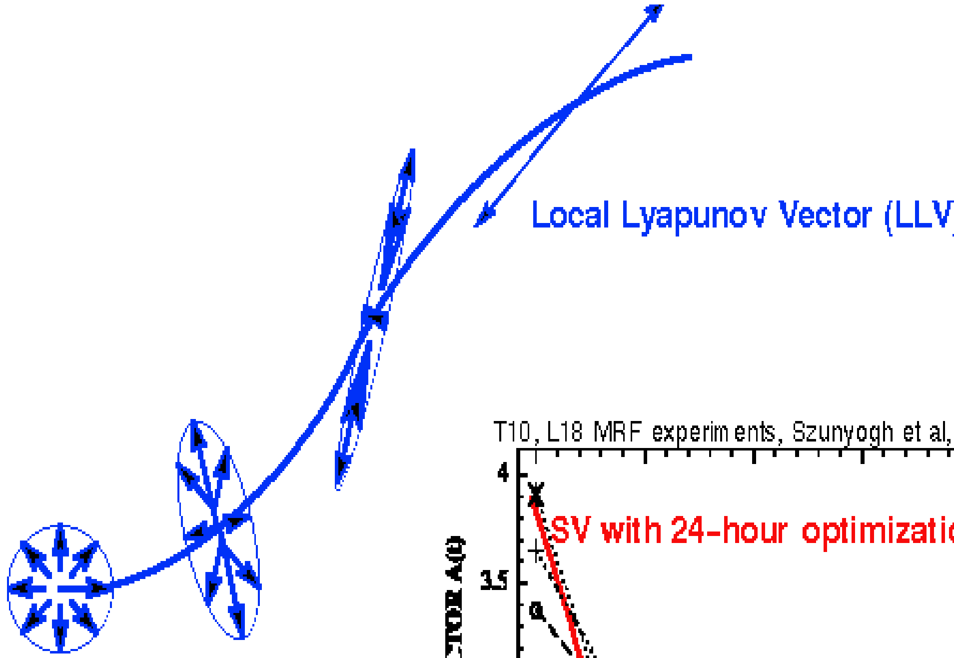
ESTIMATING AND SAMPLING INITIAL ERRORS: THE BREEDING METHOD

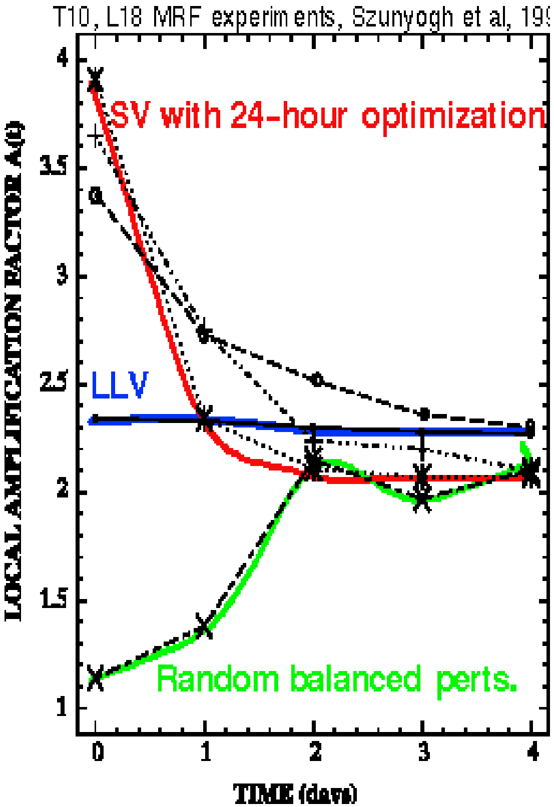
- **DATA ASSIM:** Growing errors due to cycling through NWP forecasts
- **BREEDING:** - Simulate effect of obs by rescaling nonlinear perturbations
  - Sample subspace of most rapidly growing analysis errors
    - Extension of linear concept of Lyapunov Vectors into nonlinear environment
    - Fastest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



LYAPUNOV, SINGULAR, AND BRED VECTORS

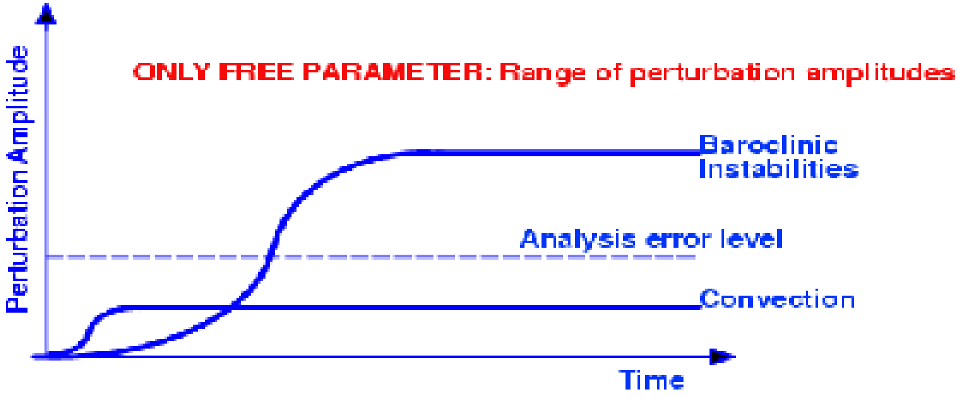
- **LYAPUNOV VECTORS (LLV):**
  - Linear perturbation evolution
  - Fast growth
  - Sustainable
  - Norm independent
  - Spectrum of LLVs
- **SINGULAR VECTORS (SV):**
  - Linear perturbation evolution
  - Fastest growth
  - Transitional (optimized)
  - Norm dependent
  - Spectrum of SVs
- **BRED VECTORS (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 typical perturbation amplitudes is only free parameter

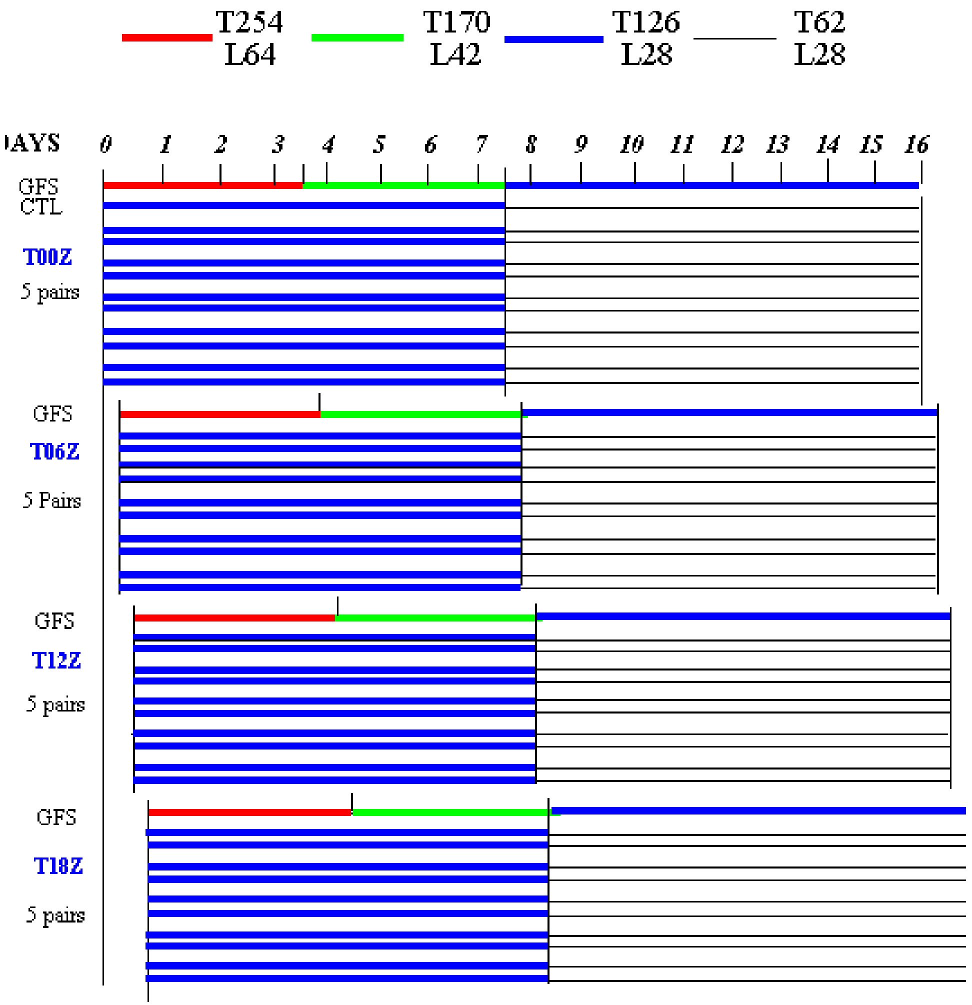


NCEP GLOBAL ENSEMBLE FORECAST SYSTEM

CURRENT *(APRIL 2004)* SYSTEM

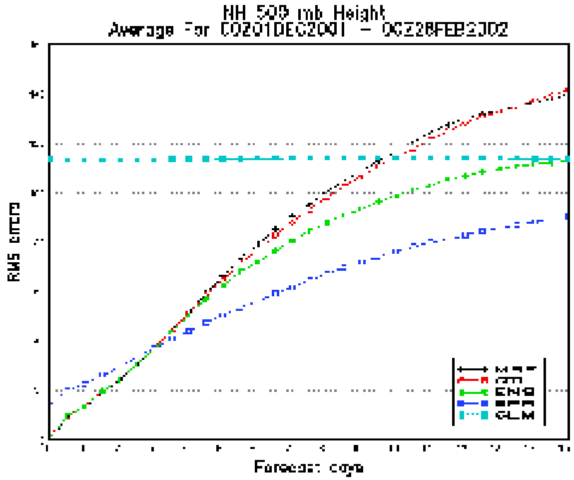
- 10 members out to 16 days
- 4 times daily
- T126 out to 7.5 days
- Model error not yet represented

- **PLANS**
- ***Initial perturbations***
  - Rescale bred vectors via ET
  - Perturb surface conditions
- ***Model errors***
  - Push members apart
  - Multiple physics (combinations)
  - Change model to reflect uncertainties
- ***Post-processing***
  - Multi-center ensembles
  - Calibrate 1^{st} & 2^{nd} moment of pdf
  - Multi-modal behavior?

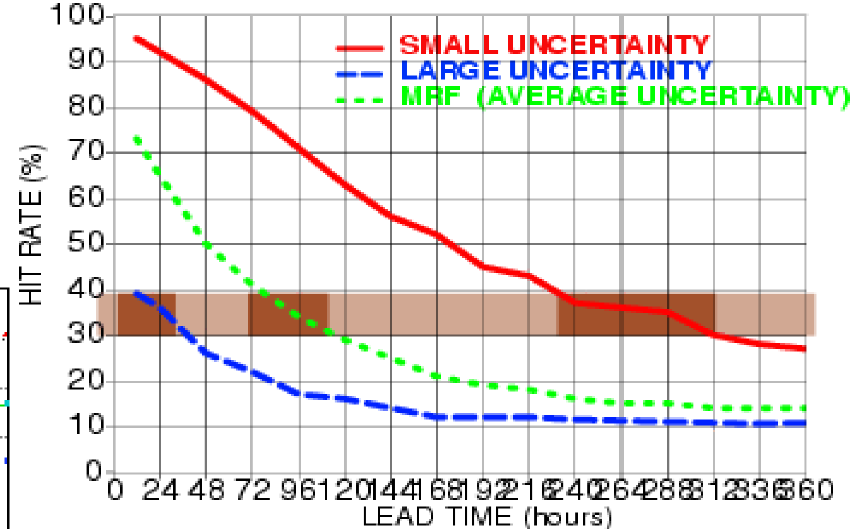


ADVANTAGES OF USING ENSEMBLE (VS. CONTROL) FCSTS

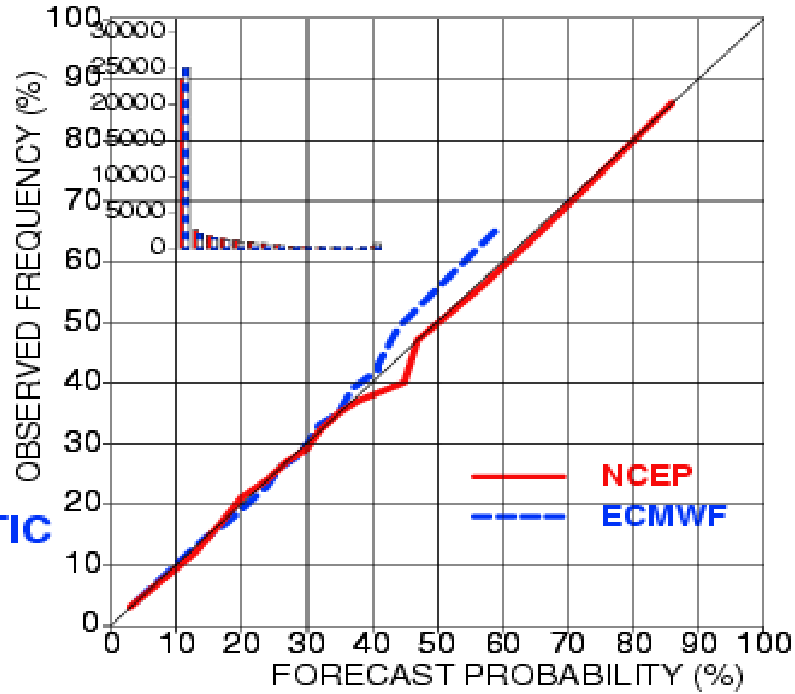
1) IMPROVED EXPECTED VALUE FORECAST



2) CASE DEPENDENT UNCERTAINTY ESTIMATE



3) DETAILED PROBABILISTIC FORECAST



RESOLUTION OF ENSEMBLE BASED PROB. FCSTS

QUESTION:

What are the typical **variations in foreseeable forecast uncertainty?**

What variations in predictability can the ensemble resolve?

METHOD:

Ensemble mode value to distinguish high/low predictability cases

Stratify cases according to ensemble mode value –

Use 10–15% of cases when ensemble is highest/loewest

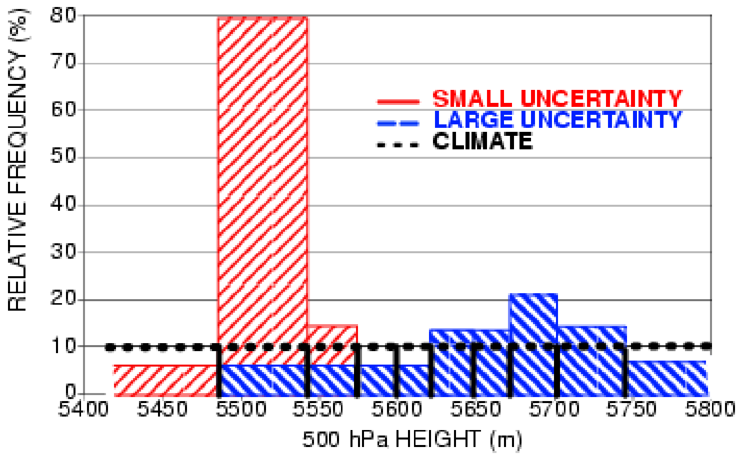
DATA:

NCEP **500 hPa NH extratropical ensemble fcsts** for March–May 1997

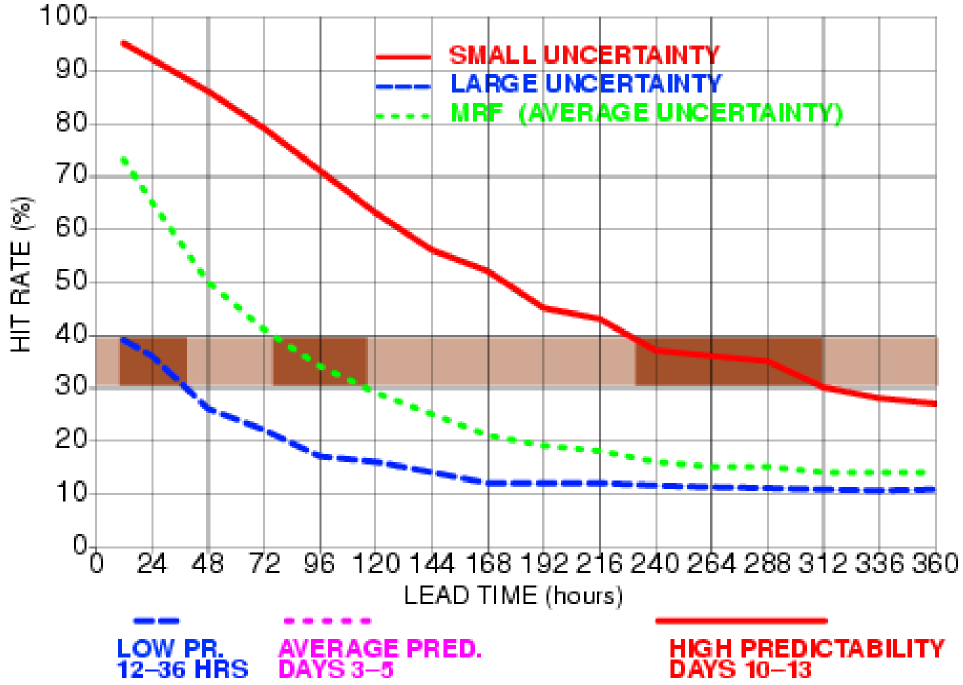
14 perturbed fcsts and high resolution control

VERIFICATION:

Hit rate for ensemble mode and hires control fcst



SEPARATING HIGH VS. LOW UNCERTAINTY FCSTS



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

HIT RATES FOR 1–DAY FCSTS

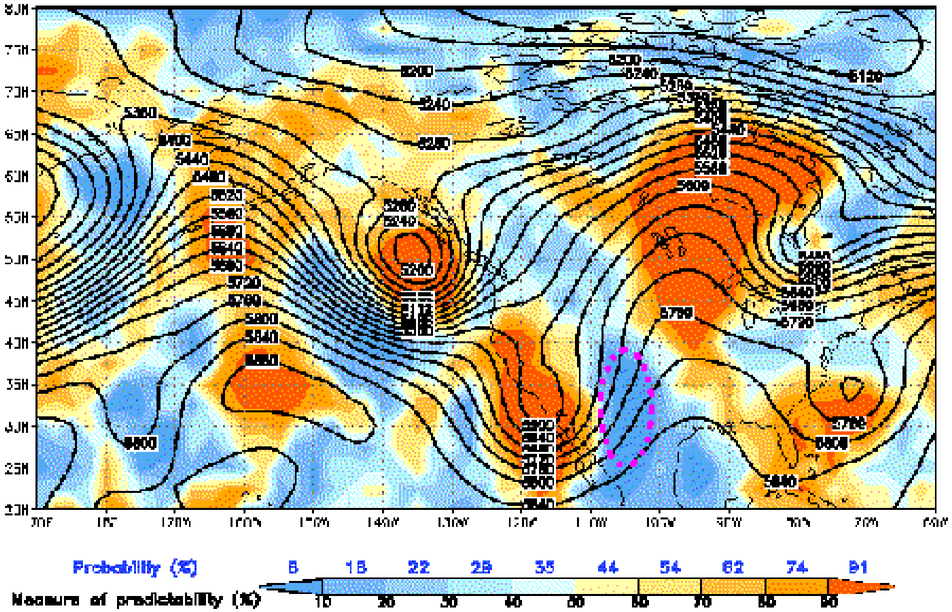
*CAN BE **AS LOW AS 36%**, OR **AS HIGH AS 92%***

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

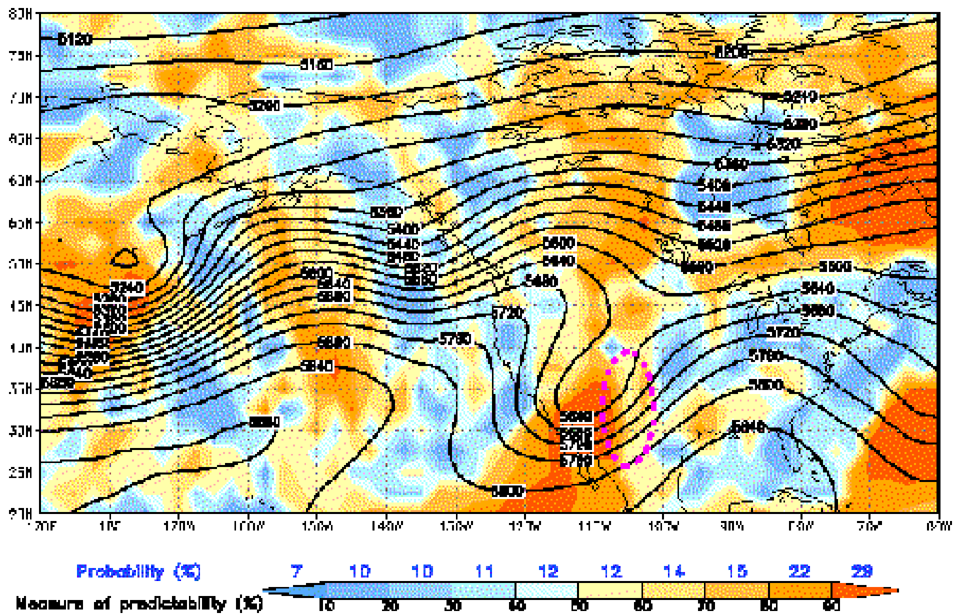
1–2% OF ALL DAYS THE 12–DAY FCST CAN BE MADE WITH MORE CONFIDENCE THAN THE 1–DAY FCST

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

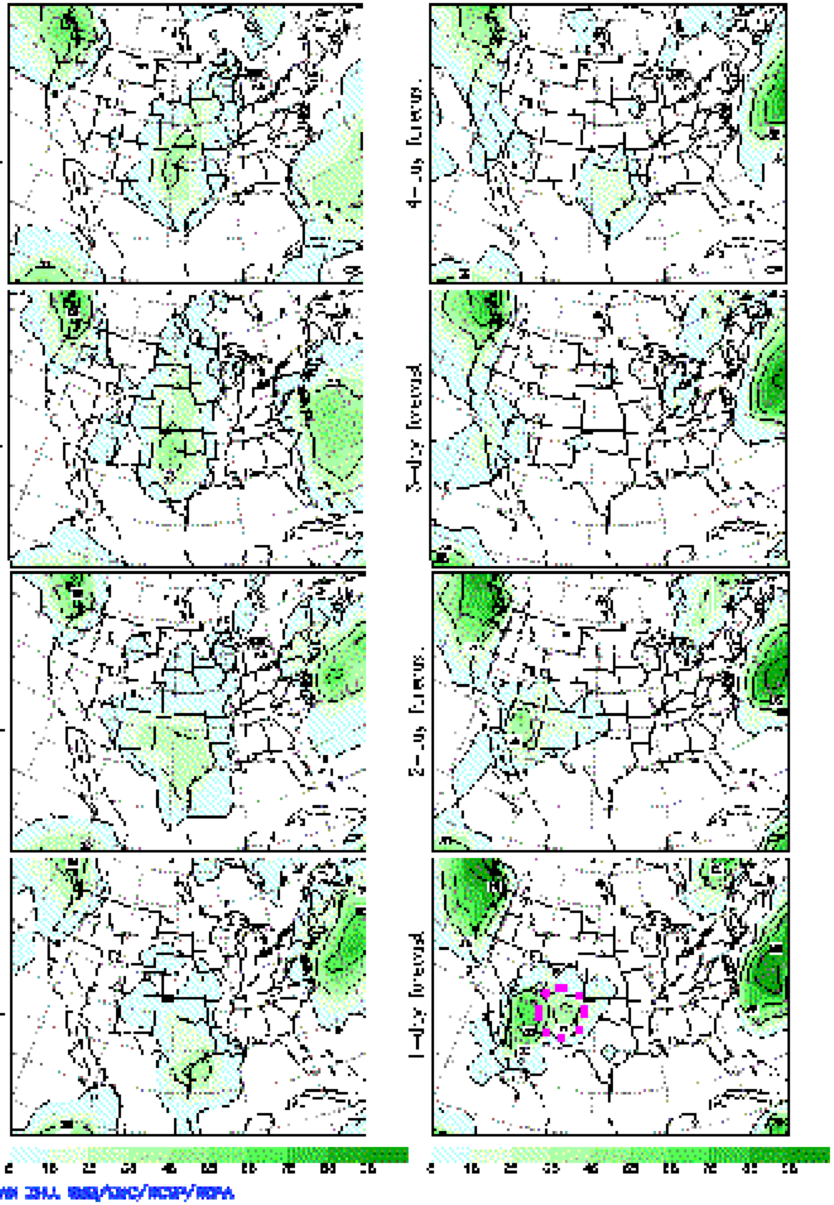
Relative measure of predictability (colors)
for ensemble mean forecast (contours) of 500 hPa height
ini: 2000102700 valid: 2000102800 fcst: 24 hours



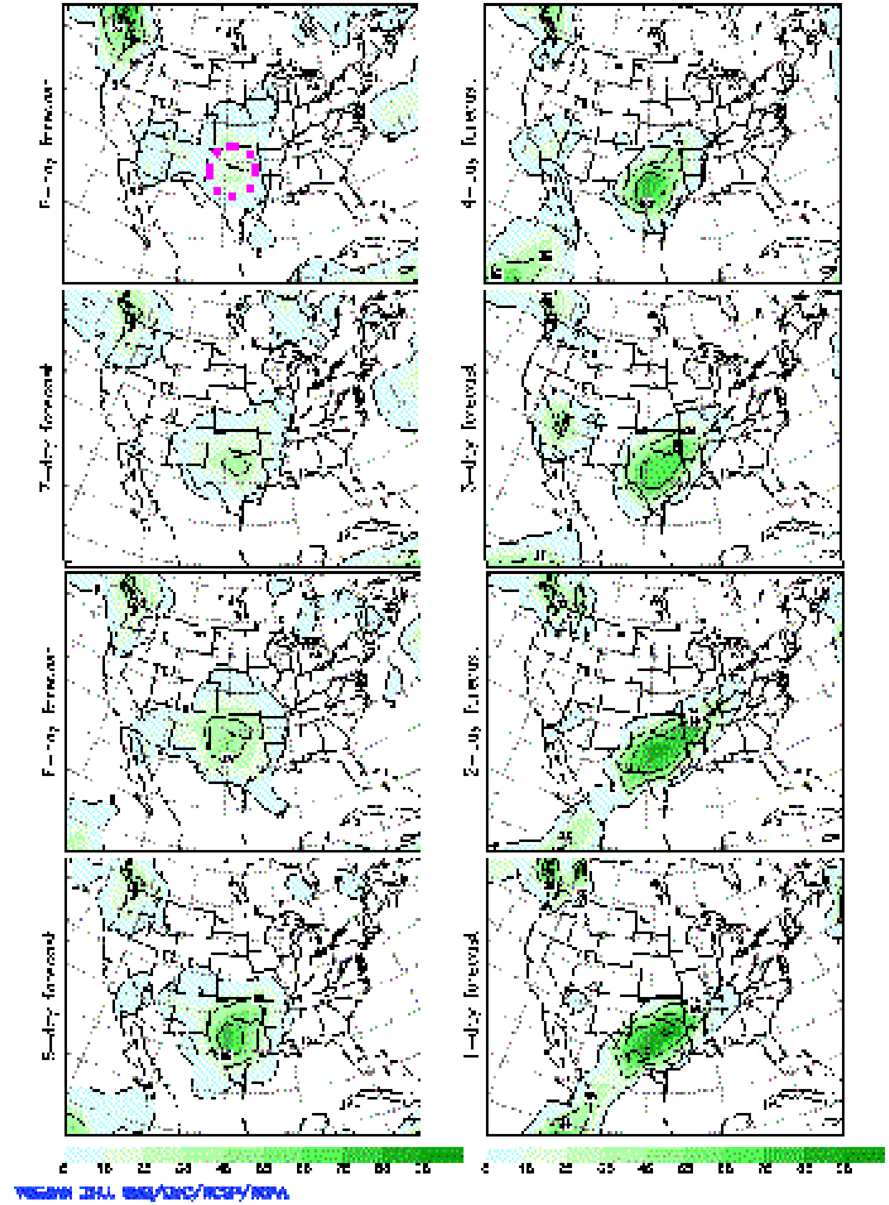
Relative measure of predictability (colors)
for ensemble mean forecast (contours) of 500 hPa height
ini: 2000102700 valid: 2000110400 fcst: 192 hours



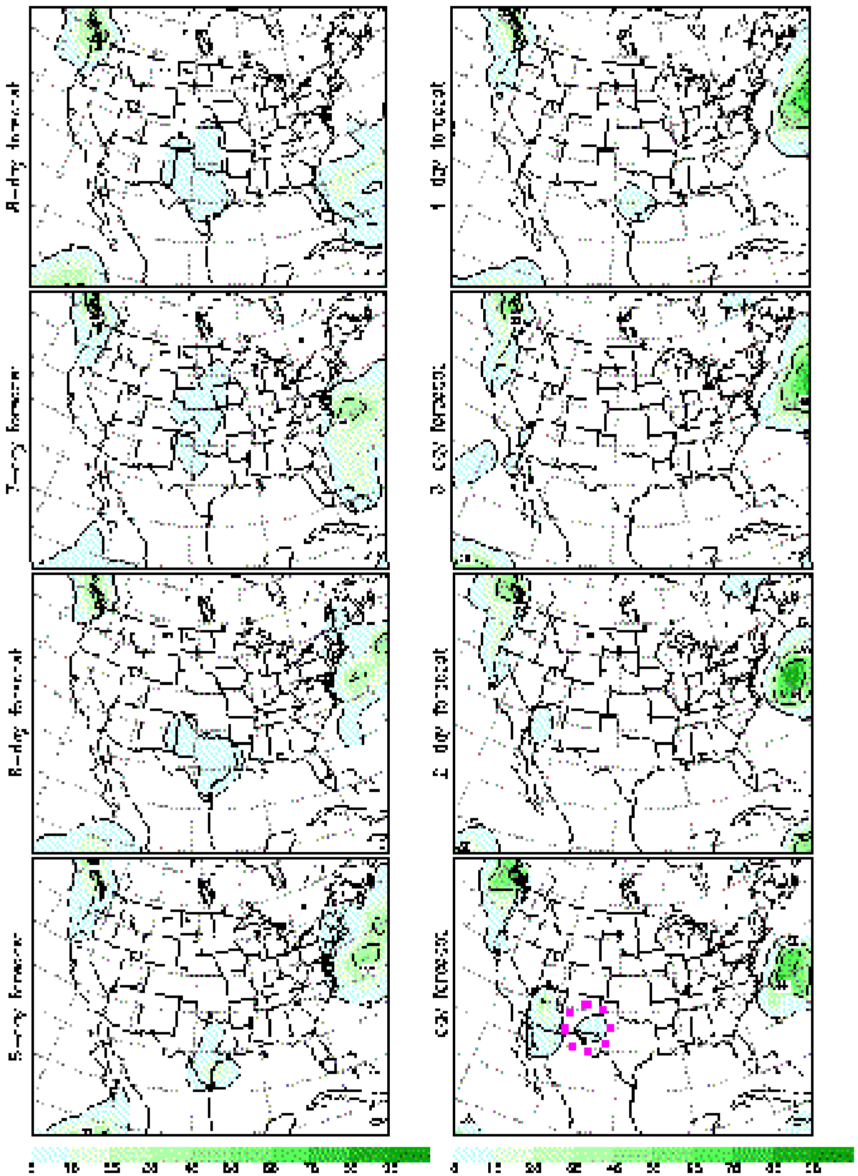
Ens Prob of Precip Amount Exceeding 0.5 inch (12.7 mm/day)
Valid Period: 2000102712–2000102812



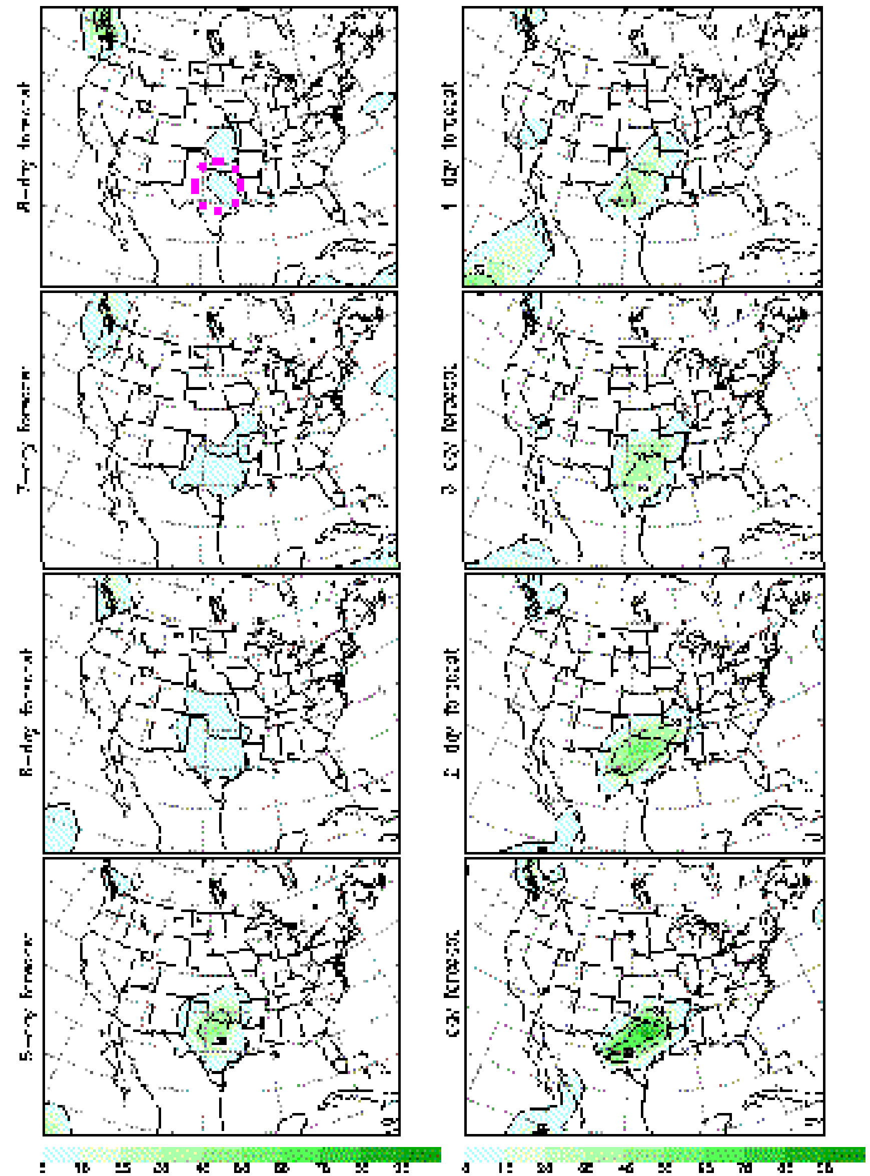
Ens Prob of Precip Amount Exceeding 0.5 inch (12.7 mm/day)
Valid Period: 2000110312–2000110412



Ens Prob of Precip Amount Exceeding 1.0 inch (25.4 mm/day)
Valid Period: 2000102712-2000102812



Ens Prob of Precip Amount Exceeding 1.0 inch (25.4 mm/day
Valid Period: 2000110312-2000110412



COMPARISON OF ECMWF, MSC, AND NCEP ENSEMBLES

	MSC	ECMWF	NCEP
Pj (model uncertainty)	2 models + Diff. Ph. Par.	Pj=P0 (single model)	Pj=P0 (single model)
dPj (random mod err)	2 models + Diff. Ph. Par.	dPj=rj*Pj (stoch. physics)	dPj=0
Aj	2 models	Aj=A0 (single model)	Aj=A0 (single model)
oj (obs error)	Random perturbations	-	-
ej (initial uncertainty)	ej from Anal. Cycles	ej=e0+dej(SV)	ej=e0+dej(BV)
hor-res HRES control	-	-	T170(d0-7)>T126(d7-16)
hor-res control	TL149	TL255 (d0-10)	T126(d0-3.5)>T62(d3.5-16)
hor-res pert members	TL149	TL255 (d0-10)	T126(d0-3.5)>T62(d3.5-16)
vertical levels (c&pf)	23 and 41, 28	40	28
top of the model	10hPa	10hPa	3hPa
perturbed members	16	50	10
forecast length	10 days	10 days	16 days
daily frequency	00 UTC	12 UTC (00 UTC exp)	00 and 12 UTC
operational impl.	February 1998	December 1992	December 1992

PATTERN ANOMALY CORRELATION (PAC)

METHOD: Compute standard PAC for

- Ensemble mean & Control fcsts

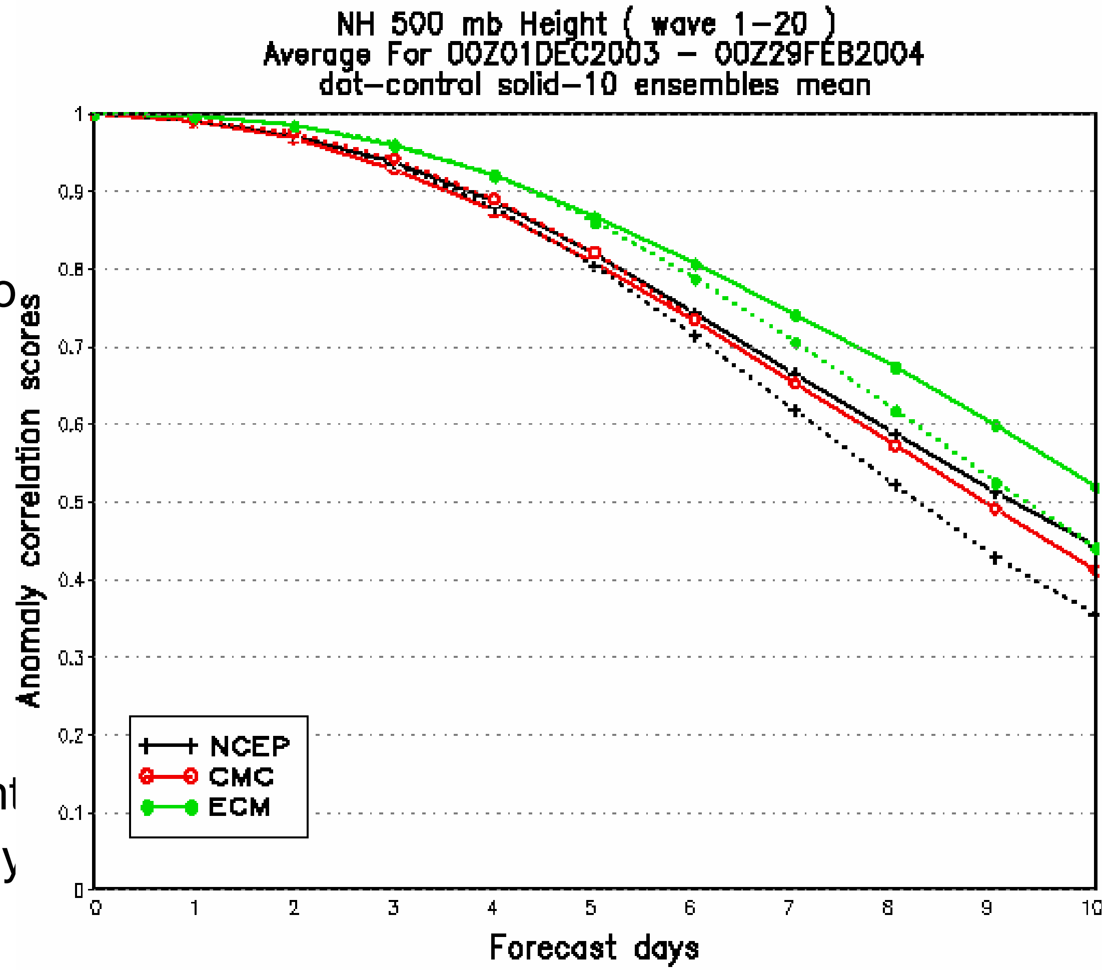
EVALUATION

Higher control score due to better:

- Analysis + NWP model

Higher ensemble mean score due to

- Analysis, NWP model, AND
- Ensemble techniques



RESULTS

CONTROL

- **ECMWF** best throughout
  - Good analysis/model

ENSEMBLE VS. CONTROL

- **CANADIAN** poorer than **hires** cont
  - Poorer (old OI) ensemble analy
- **NCEP** performs well compared to control
  - Despite lack of model perturbations

ENSEMBLE

- **ECMWF** best throughout
  - Good analysis/model?

Y. Zhu et al.

PERTURBATION VS. ERROR CORRELATION ANALYSIS (PECA)

METHOD: Compute correlation between ens perturbtns and error in control fcst for

- Individual members
- Optimal combination of members
- Each ensemble
- Various areas, all lead time

EVALUATION: Large correlation indicates ens captures error in control forecast

- Caveat – errors defined by analysis

RESULTS:

- **Canadian** best on large scales
  - Benefit of model diversity?
- **ECMWF** gains most from combinations
  - Benefit of orthogonalization?
- **NCEP** best on small scale, short term
  - Benefit of breeding (best estimate initial error)?
- PECA increases with lead time
  - Lyapunov convergence
  - Nonlinear saturation
- Higher values on small scales

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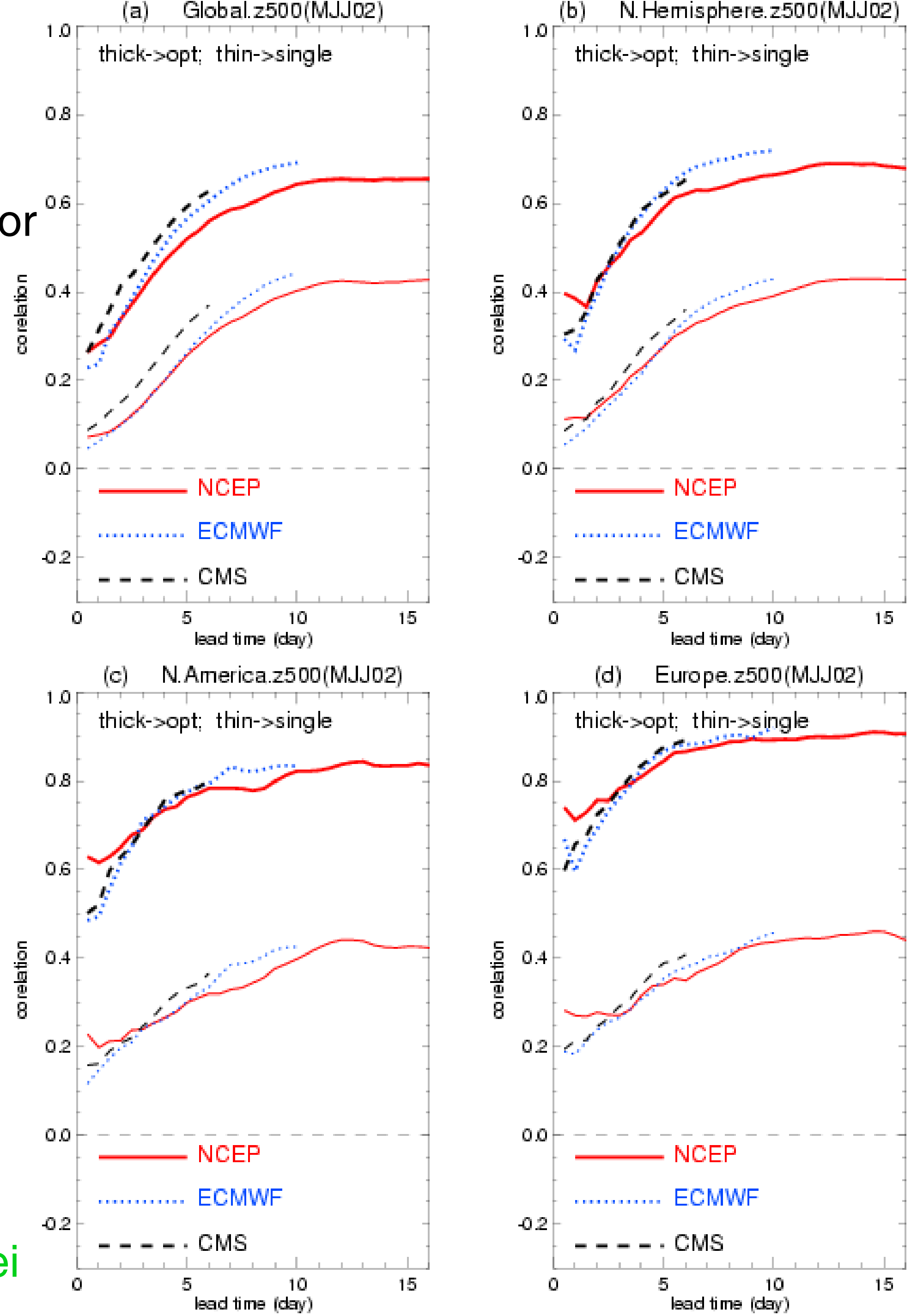


EXPLAINED ERROR VARIANCE AS A FUNCTION OF ENSEMBLE SIZE

METHOD: Compute correlation between ens perturbtns and error in control fcst for

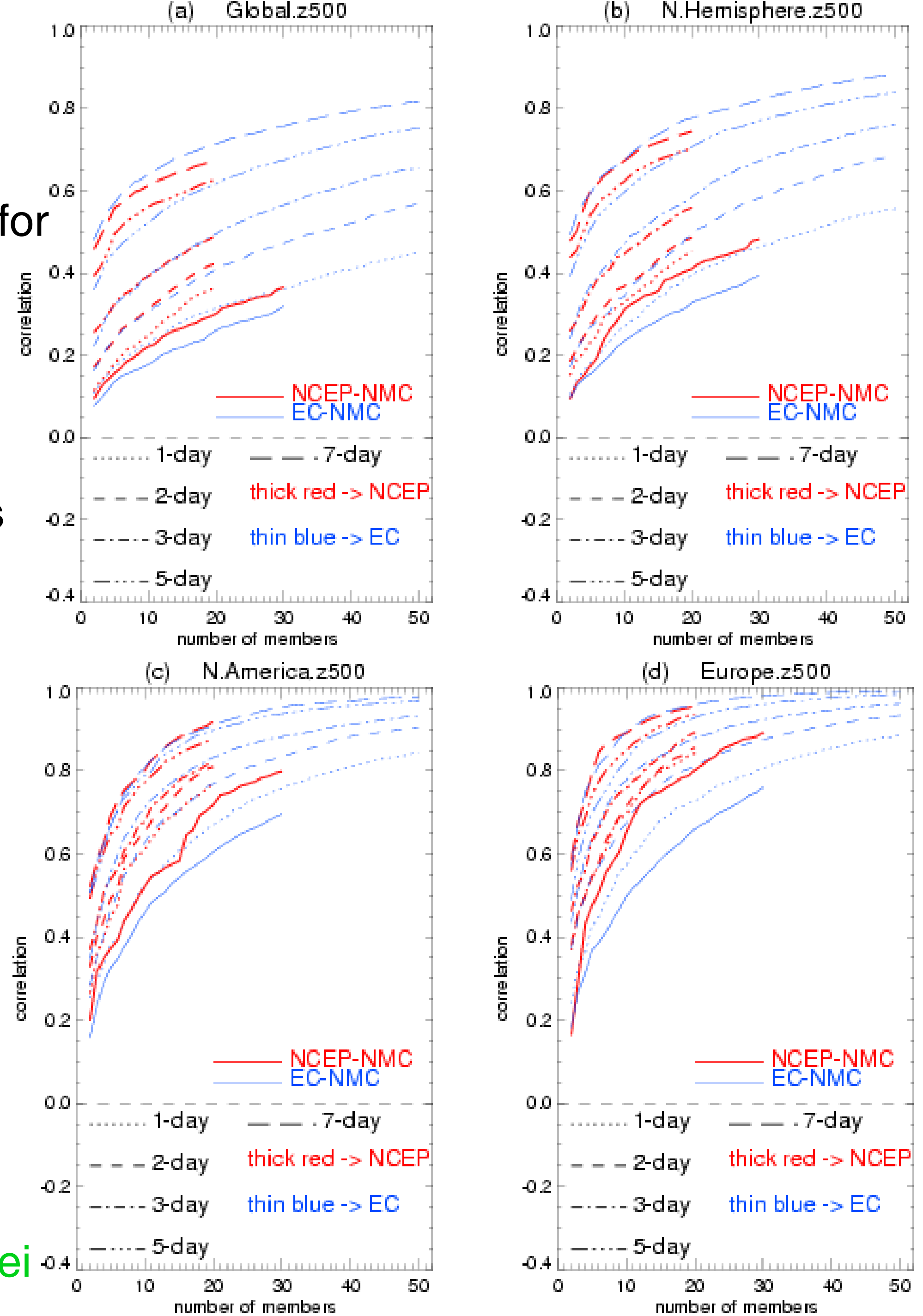
- Individual members
- Optimal combination of members
- Each ensemble
- Various areas, all lead time

EVALUATION: Large correlation indicates ens captures error in control forecast

- Caveat – errors defined by analysis

RESULTS:

- **SPATIAL SCALES –**
  - Global/hemispheric scales – No saturation seen up to 50
  - Continental scales – Gains level off, especially at longer lead
- **LEAD TIME –**
  - Very little gain beyond 30 members at longer ranges



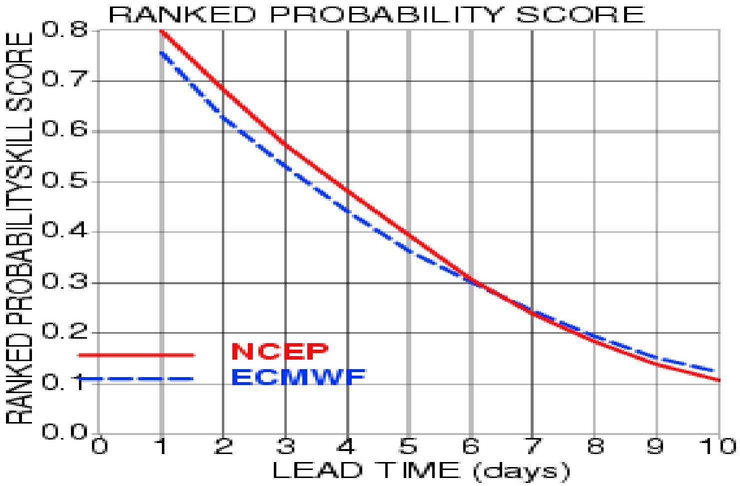
M. Wei

SUMMARY OF 3-WAY INTERCOMPARISON RESULTS

Results depend on time period

CONTROL FORECAST

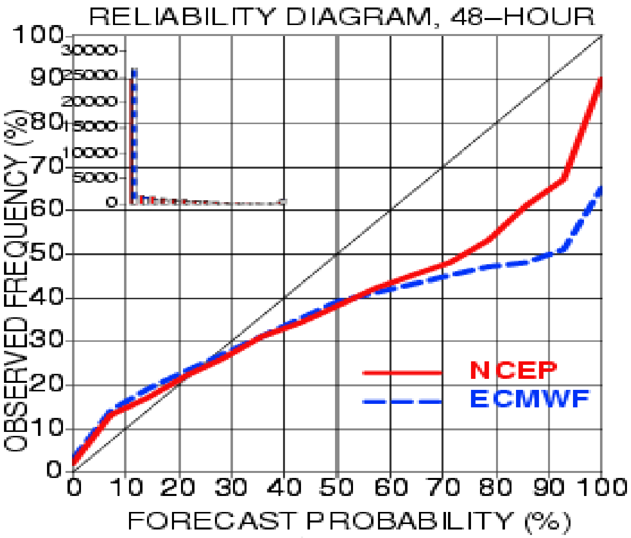
- **ECMWF** best overall control forecast
  - Best analysis/forecast system



Ranked probability skill score for December 1995 – February 1996.

ENSEMBLE FORECAST SYSTEM

- Difficult to separate effect of analysis/model quality
- **ECMWF** best overall performance
- **NCEP**
  - Days 1-3 - Very good (best for PECA)
    - Value of breeding?
  - Beyond day 3 – Poorer performance
    - Lack of model perturbations
- **CANADIAN**
  - Days 6-10 – Better than NCEP
    - Value of model diversity?



Reliability diagram for 48–hour lead time. Forecast probabilities are based on how many ensemble members fell in any particular climate bin at each gridpoint. Insert in upper left corner shows in how many events a particular forecast probability was used. December 1995– February 1996.

EXISTING/PROPOSED APPROACHES

FIRST GENERATION INITIAL PERTURBATION TECHNIQUES

	PERTURBED OBSERVATIONS ***(MSC, Canada)***	***BREEDING with Regional Rescaling*** ***(NCEP, USA)***	***SINGULAR VECTORS with Total Energy*** ***(ECMWF)***
ESTIMATION	Realistic through sample, case dependent patterns & amplitudes	Fastest growing subspace, case dependent patterns	No explicit estimate, not flow dependent
SAMPLING	Random for all errors, incl. non-growing, potentially hurting short-range performance	Random in subspace of fastest growing errors; *Some dependence among perts.*	Directed, dynamically fastest growing in future
CONSISTENCY BETWEEN ENS & DA SYSTEMS	Very good; quality of DA lagging behind 3DVAR?	*Time-constant variance due to use of fixed mask*	Poor, potentially hurting short-range performance

EXISTING/PROPOSED APPROACHES - 2

SECOND GENERATION INITIAL PERTURBATION TECHNIQUES

	ETKF, perts influenced by fcsts and observed data	***ET/BREEDING with Analysis Error Variance Estimate from DA***	***SINGULAR VECTORS with Hessian norm***
ESTIMATION	Fast growing subspace, case dependent patterns & amplitudes	Fastest growing subspace, case dependent patterns & amplitudes	Case dependent variance, climatologically fixed covariance
SAMPLING	Orthogonal in subspace of observations	*Orthogonal in analysis covariance norm*	Directed, dynamically fastest growing in future
CONSISTENCY BETWEEN ENS & DA SYSTEMS	Very good; quality of DA lagging 4D-VAR?	*Good; Error variance: DA=>ens; Error covariance: Ens=>DA*	Climatologically consistent

COMPARISON OF DIFFERENT METHODS

GRADUAL CONVERGENCE OF METHODS?

- *ETKF with no observation perturbation = Breeding with orthogonalization and rescaling consistent with varying observational network*
- COMMON CONCEPT:
  - Perturbations cycled dynamically through use of nonlinear integrations
  - Bred Vectors (Toth & Kalnay 1993) = Nonlinear Lyapunov Vectors (Boffetta et al 1998)

- *Evolved SVs constrained by analysis error covariance (Hessian SVs) ~ Bred perturbations*
- COMMON CONCEPT:
  - With realistic initial constraint, SV dynamics ~ Lyapunov dynamics?
  - Explore SVs in subspace of ensemble forecasts – Bishop, etc

MOTIVATION FOR EXPERIMENTS

***TWO OJECTIVES* for ensemble generation:**

1) Best quality ensemble forecasts
   - Primary objective, performance measure
2) Ensemble as consistent with data assimilation system as possible
   - Secondary objective, to facilitate use of ensemble info in DA

CONSISTENCY can be achieved by:

a) Development & use of ensemble-based DA system
   - Through THORPEX project, NCEP is collaborating with 4-5 groups on this
b) Coupling existing DA (3/4DVAR) with ensemble generation scheme
   - Goal of present study

***INTEREST* of study:**

- As long as ensemble-based DA cannot outperform other 3/4DVAR
  - Modify and couple existing DA and ensemble systems
  - Use cheap ensemble generation scheme, since full consistency is unreachable
    - Simple initial perturbation scheme driven by analysis error variance from DA
    - 3/4DVAR driven by flow dependent forecast error covariance from ensemble

DESCRIPTION OF 4 METHODS TESTED

- **BREEDING** with regional rescaling (Toth & Kalnay 1997)
  - Simple scheme to dynamically recycle perturbations
    - Variance constrained statistically by fixed analysis error estimate “mask”
      - ***Limitations:*** No orthogonalization; fixed analysis variance estimate used

- **ETKF** (Bishop et al. 2004, Wang & Bishop 2003) – used as perturbation generator (not DA)
  - Dynamical recycling as breeding, with orthogonalization in obs space
    - Variance constrained by distribution & error variance of observations
      - Constraint does not work well with only 10 ensemble members
    - Built on ETKF DA assumptions => ***NOT consistent with 3/4DVAR***

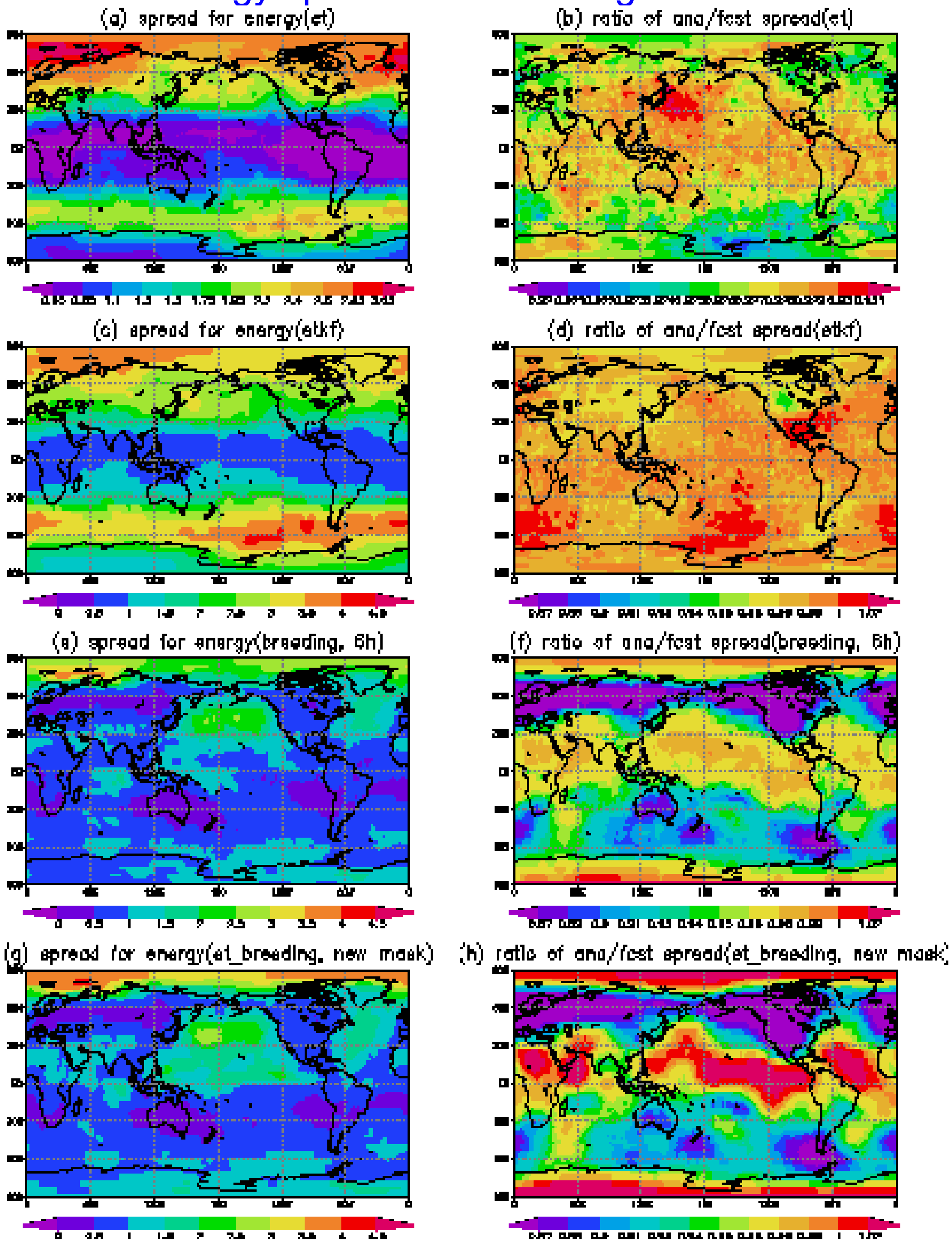
- **Ensemble Transform (ET)** (Bishop & Toth 1999)
  - Dynamical recycling as breeding, with orthogonalization
    - Variance constrained statistically by fixed analysis error estimate “mask”
      - Constraint does not work well with only 10 ensemble members

- **ET plus rescaling** = Breeding with orthogonalization, (Wei et al. 2004)
  - As ET, except variance constrained statistically by fixed analysis error estimate

EXPERIMENTS

- Time period
  - Jan 15 – Feb 15 2003
- Data Assimilation
  - NCEP SSI (3D-VAR)
- Model
  - NCEP GFS model, T126L28
- Ensemble
  - 2x5 or 10 members, no model perturbations
- Evaluation
  - 7 measures, need to add probabilistic forecast performance

Initial energy spread | Rescaling factor distribution



← ET

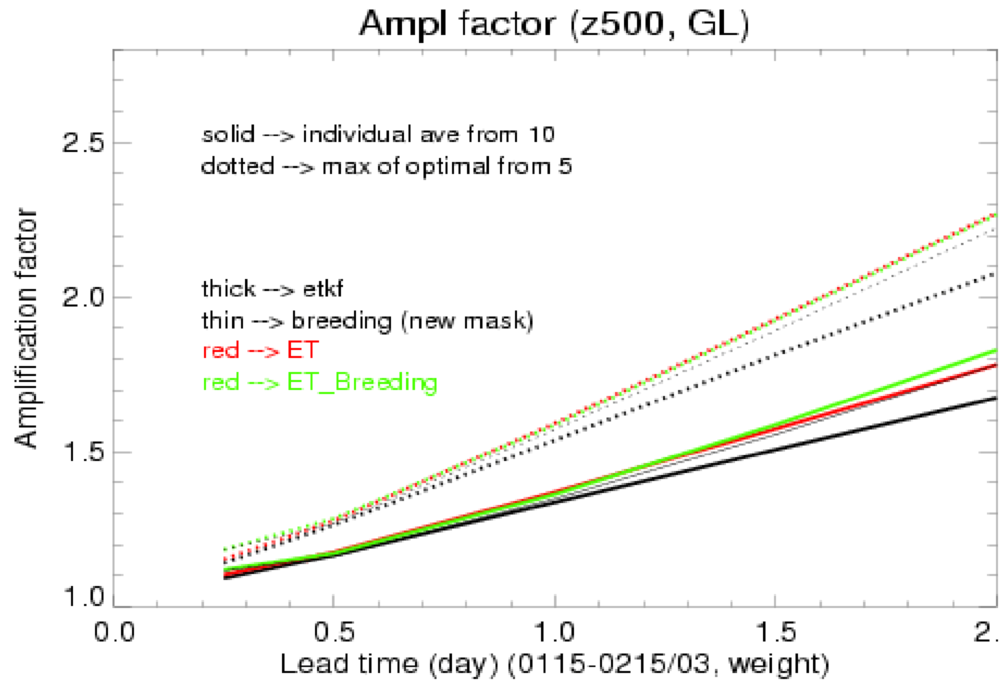
← ETKF

← Breeding

← ET+rescaling

M. Wei et al.

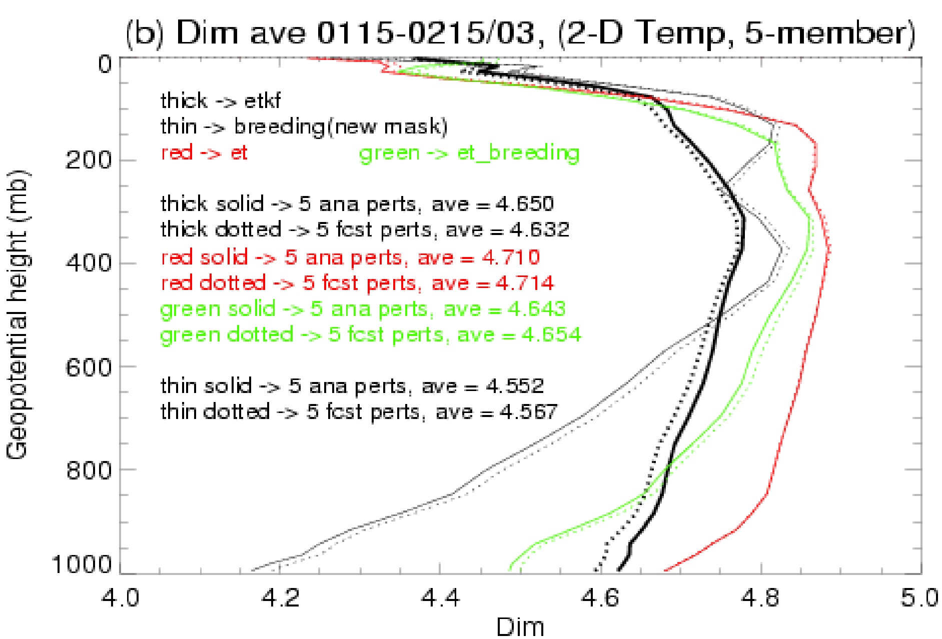
Amp Factor

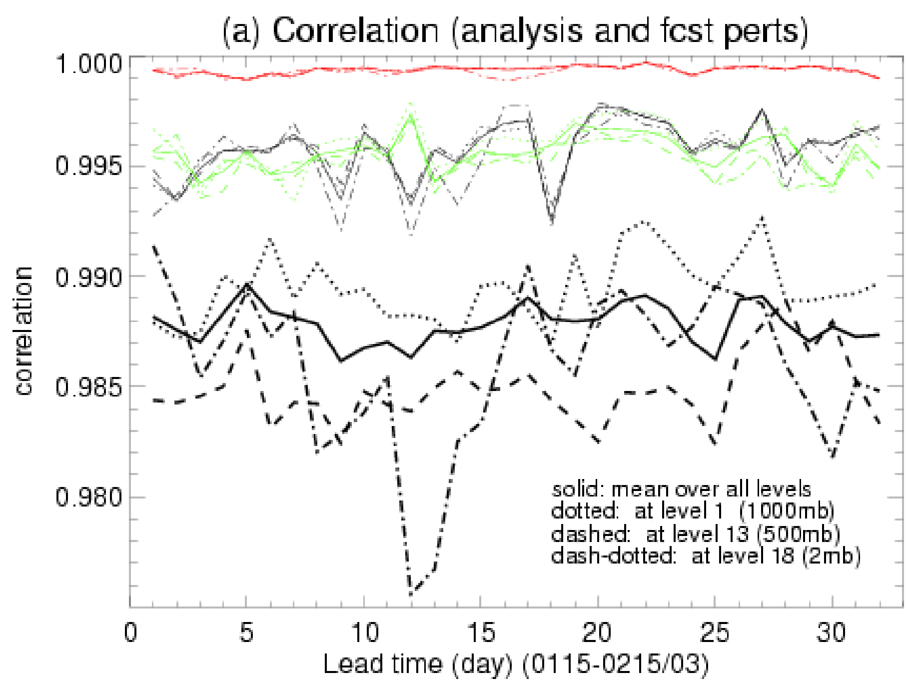


M. Wei et al.

Effective Dim

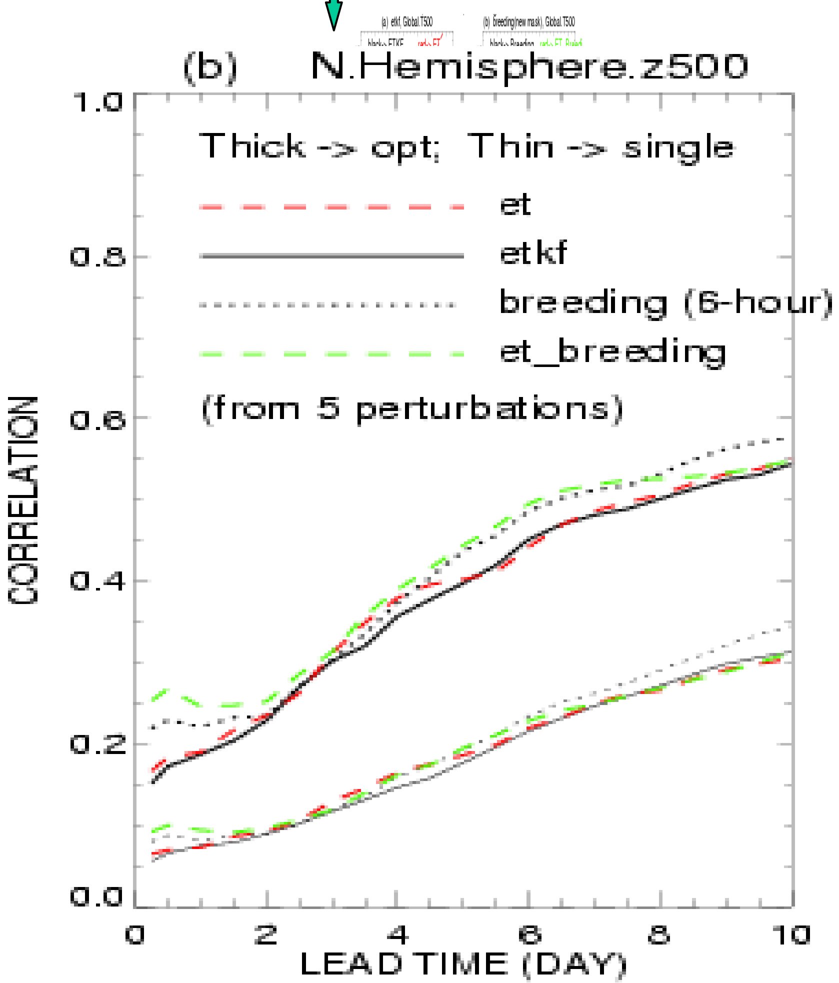
Correlation

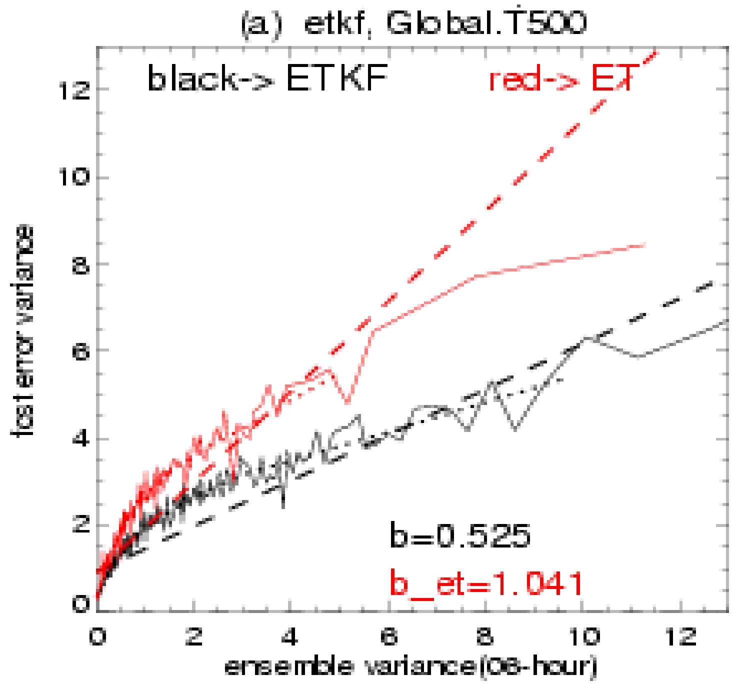


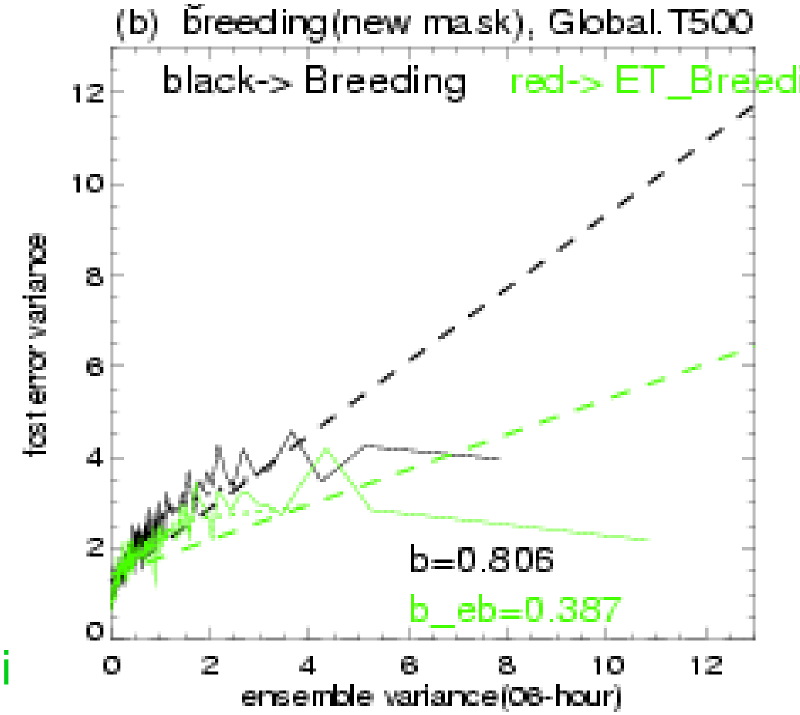


Variance

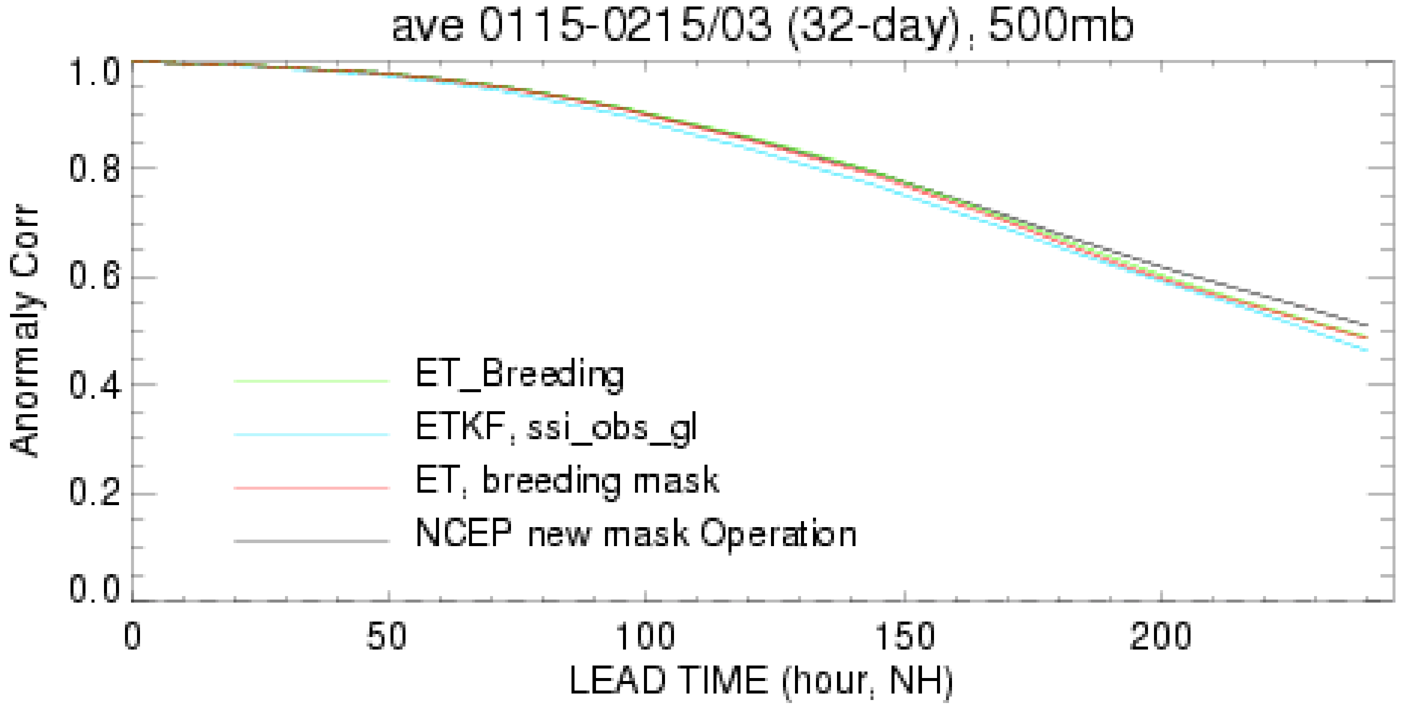
PECA



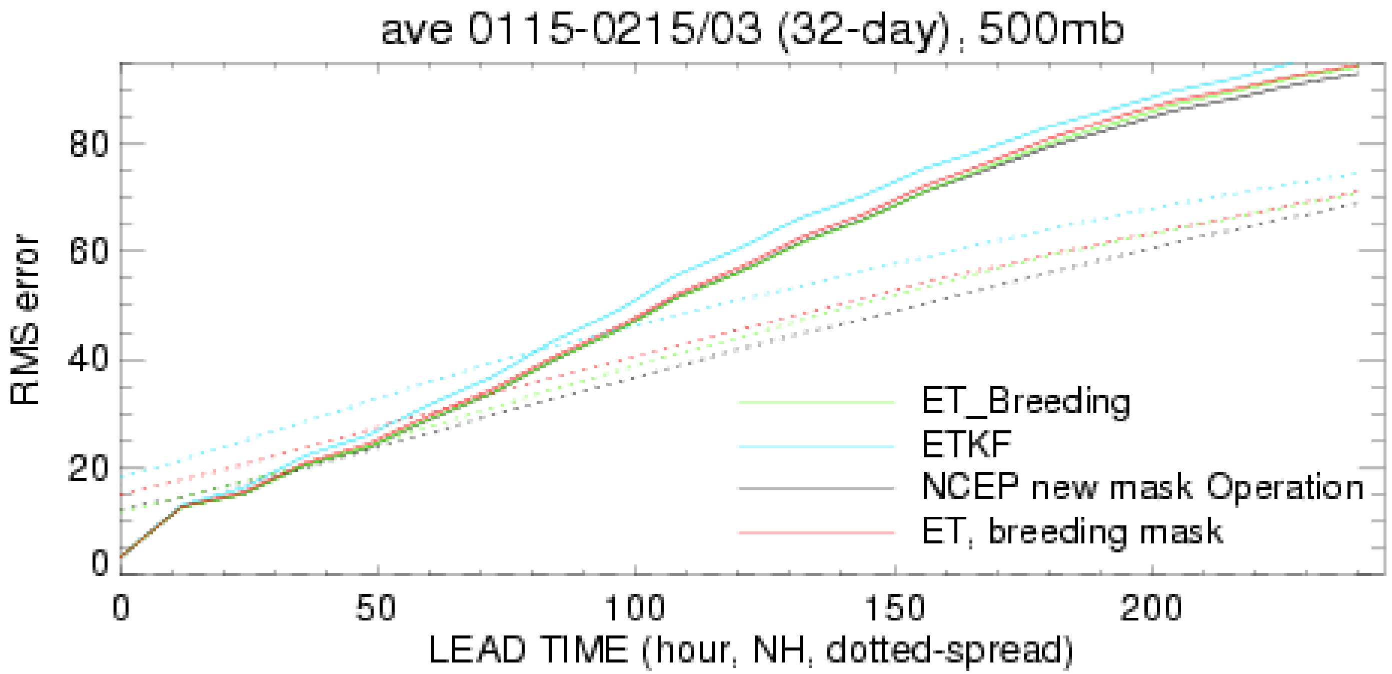




M. Wei



←AC



←RMS error

M. Wei et al.

SUMMARY OF RESULTS

- **RMSE, PAC of ensemble mean forecast –** *Most important*
  - ET+Rescaling and Breeding are best, ET worse, ETKF worst
- **Perts and Fcst error correlation** (PECA) – *Important for DA*
  - ET+Rescaling best, Breeding second
- **Explained variance** (scatterplots) – *Important for DA*
  - ET best
- **Variance distribution** (climatological, geographically)
  - Breeding, ET+Rescaling reasonable
- **Growth rate**
  - ET+Rescaling best? (not all runs had same initial variance…)
- **Effective degrees of freedom** out of 5 members
  - Minimal effect of orthogonalization
    - Breeding (no orthogonalization) =4.6
    - ET (built-in orthogonalization) =4.7
- **Time consistency** of perturbations (PAC between fcst vs. analysis perts)
  - Important for hydrologic, ocean wave, etc ensemble forcing applications
  - Excellent for all schemes, ET highest (0.999, breeding "lowest", 0.988)
    - New and very promising result for ET & ETKF
- ***OVERALL hits out of 7***
  - ET+Rescaling 4
  - ET 3
  - Breeding 2

DISCUSSION

- All tests in context of 5-10 perturbations
  - Will test with 80 members
  - Plan to experimentally exchange members with NRL
    - Will have total of 160 members
- 4-dim time-dependent estimate of analysis error variance
  - Need to develop procedure to derive from SSI 3DVAR
- ET+Rescaling looks promising
  - Extension of breeding concept with orthogonalization
    - ***JOB OF ENSEMBLE: CAPTURE THE DYNAMICS OF THE SYSTEM***
  - Orthogonalization appears to help breeding
  - Cheap procedure, also used in targeting
- If ensemble-based DA cannot beat 3/4DVAR
  - Initial ens cloud need to be repositioned to center on 3/4DVAR analysis
  - No need for sophisticated ens-based DA algorithm for generating initial perts?

Good EPS $\Longleftrightarrow$ Good DA

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

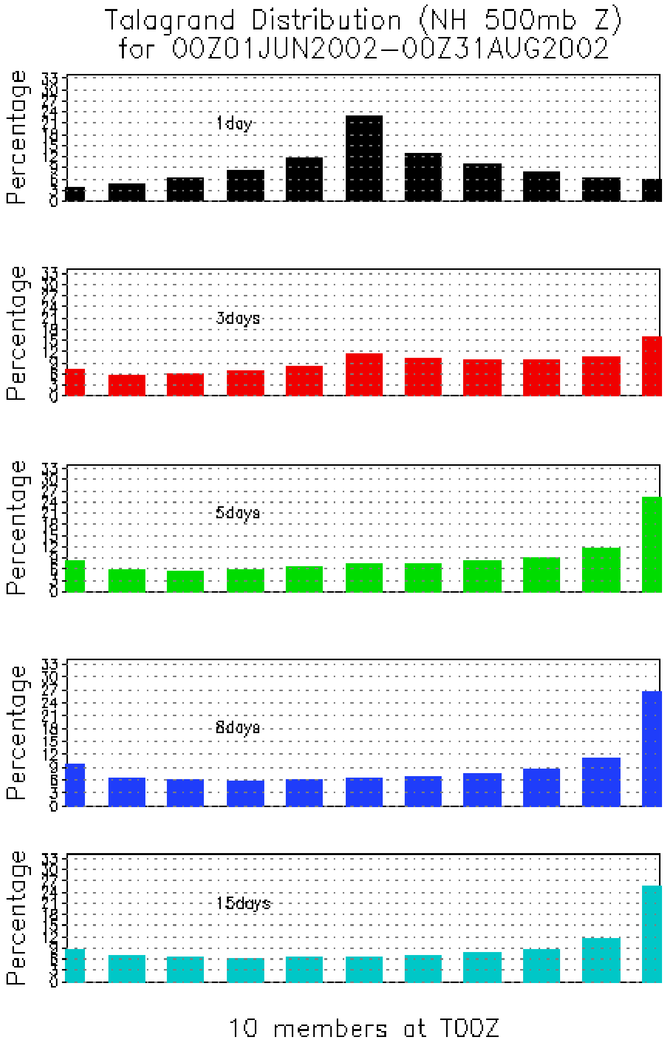
WHAT HAPPENS IF MODEL ERRORS ARE IGNORED?

Y. Zhu

NCEP ENSEMBLE RESULTS:

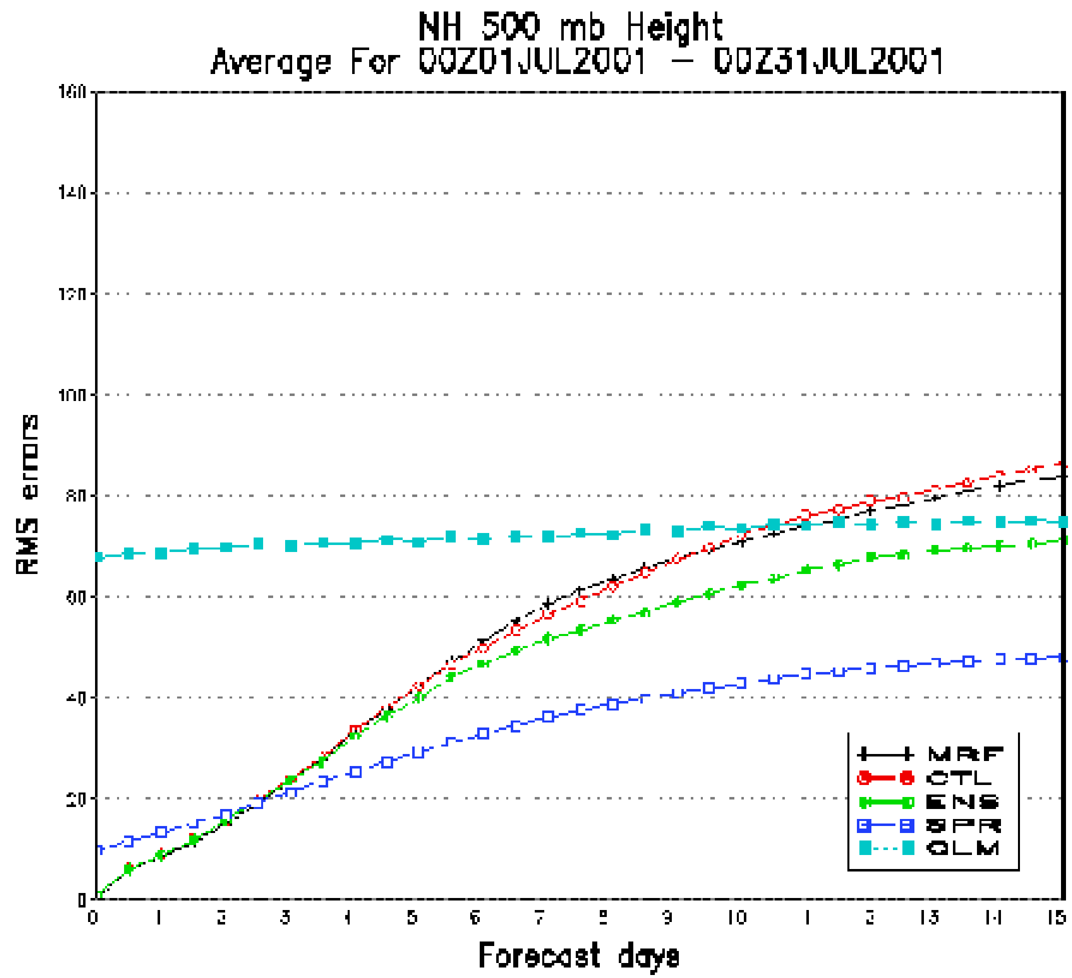
Bias in first moment

All members shifted statistically



Bias in second moment

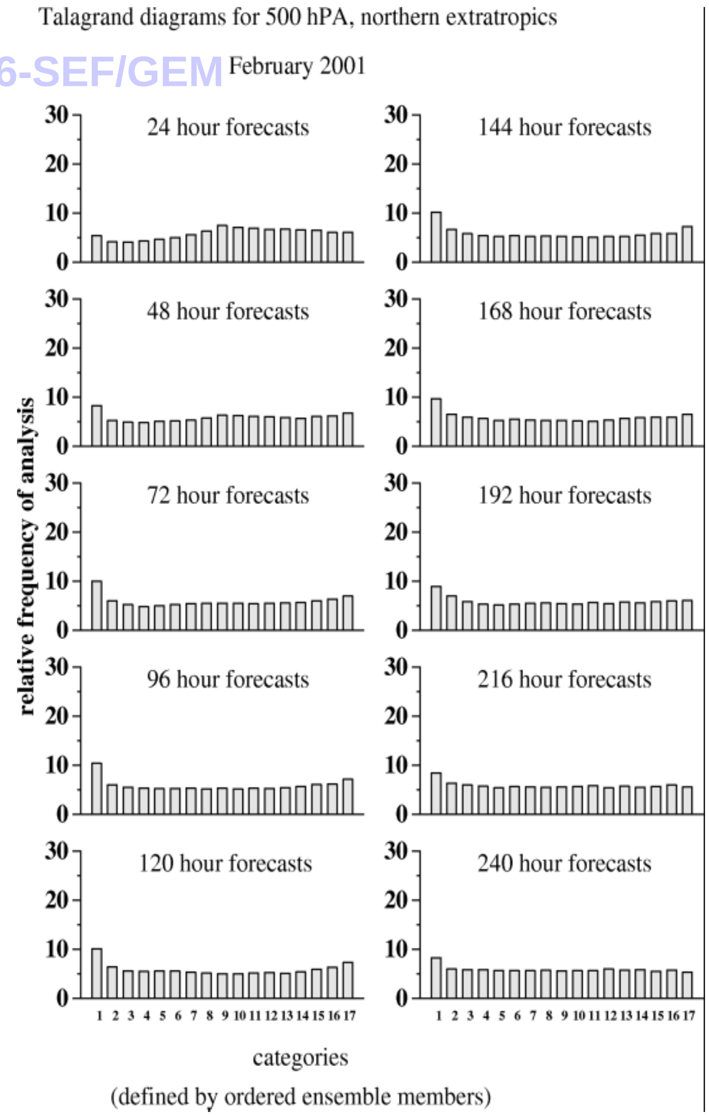
Perturbation growth lags error growth



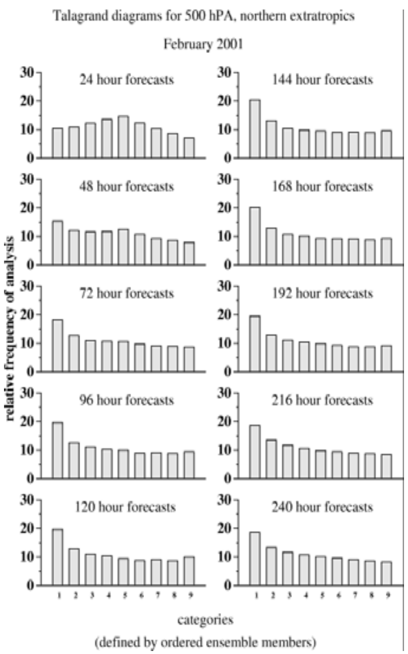
The impact of using a second model at MSC

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

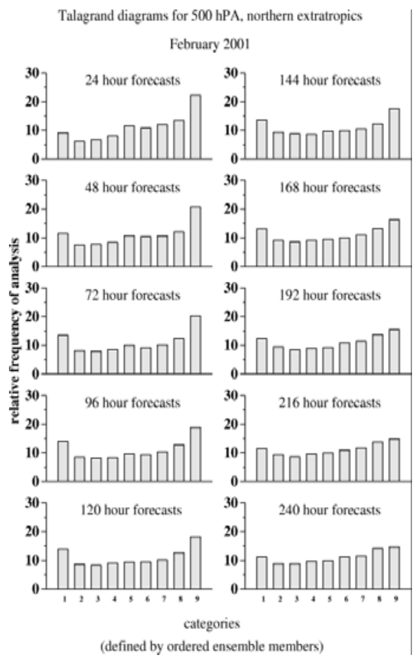
16-SEF/GEM



8-SEF



8-GEM

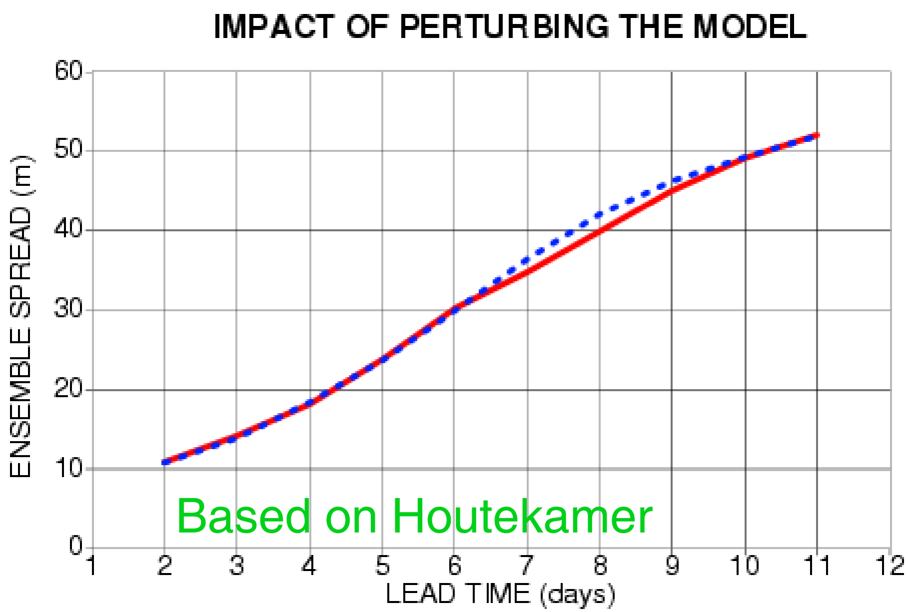


P. Houtekamer

SAMPLING FORECAST ERRORS =
REPRESENTING ERRORS DUE TO USE OF
IMPERFECT MODELS - 1

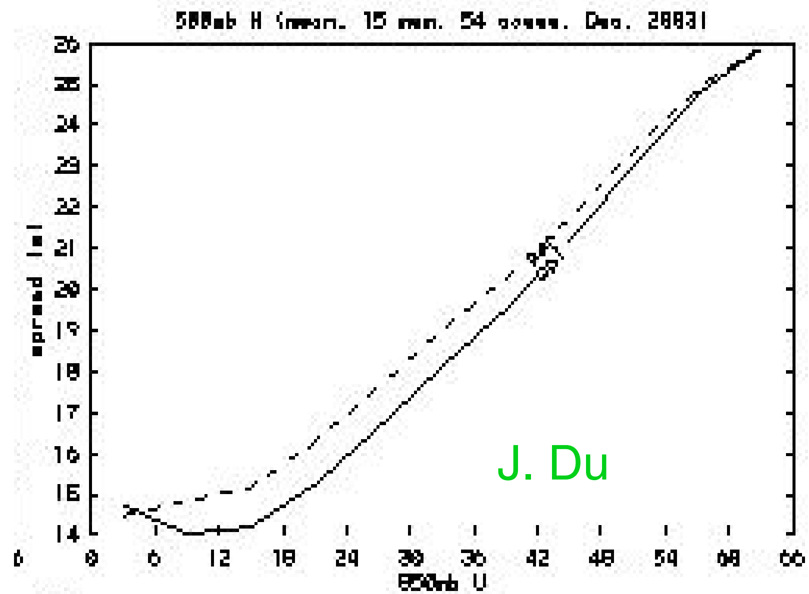
CURRENT METHODS

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

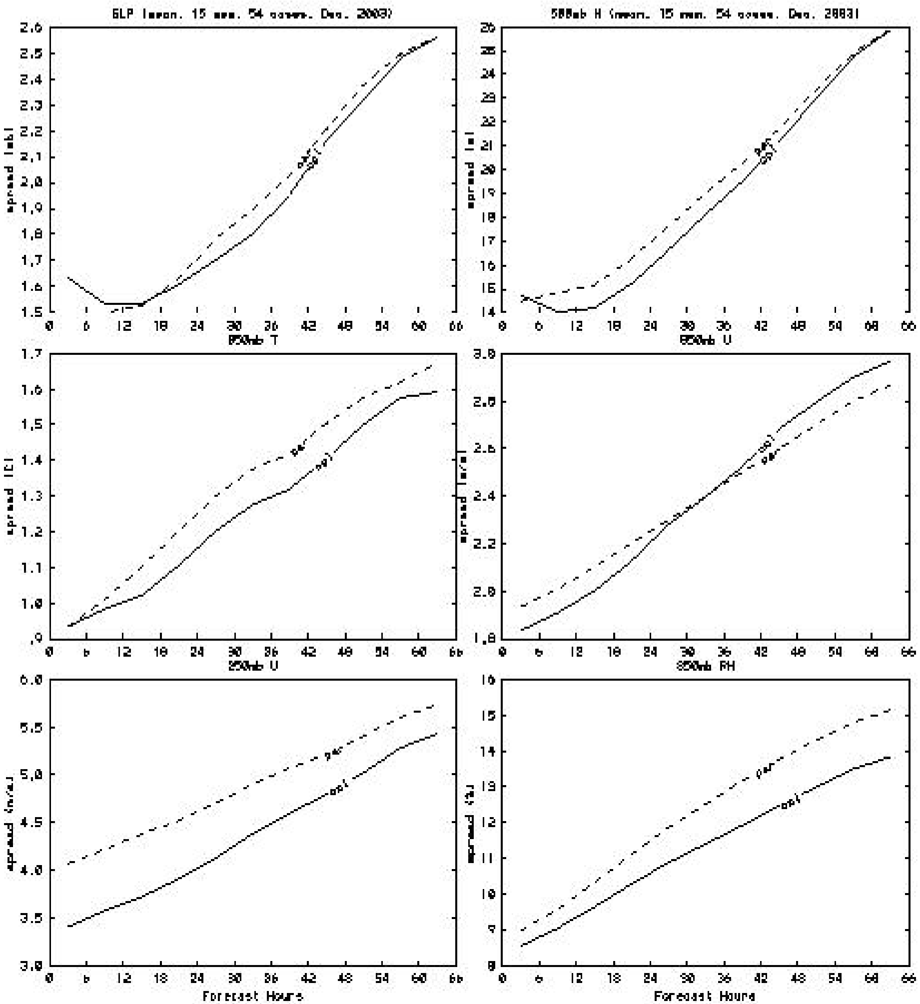


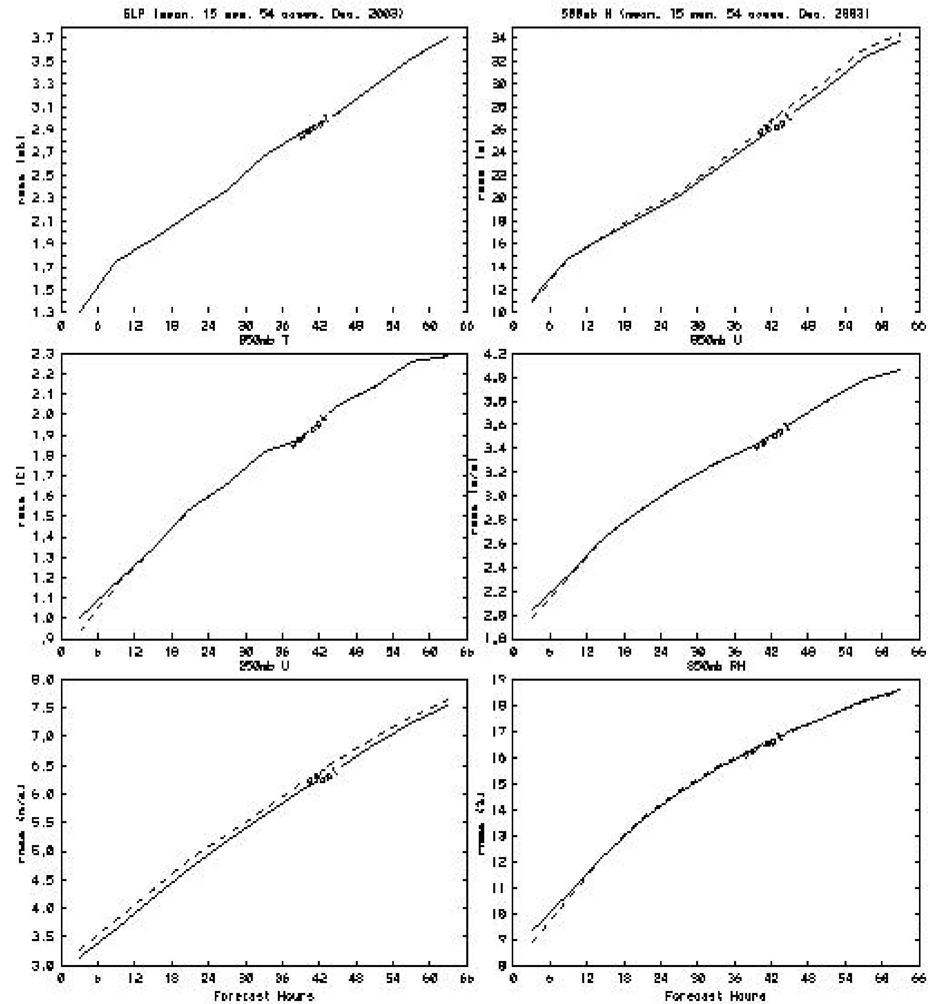
Oper: 3 model versions
Para: More model diversity

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

Spread

RMS error





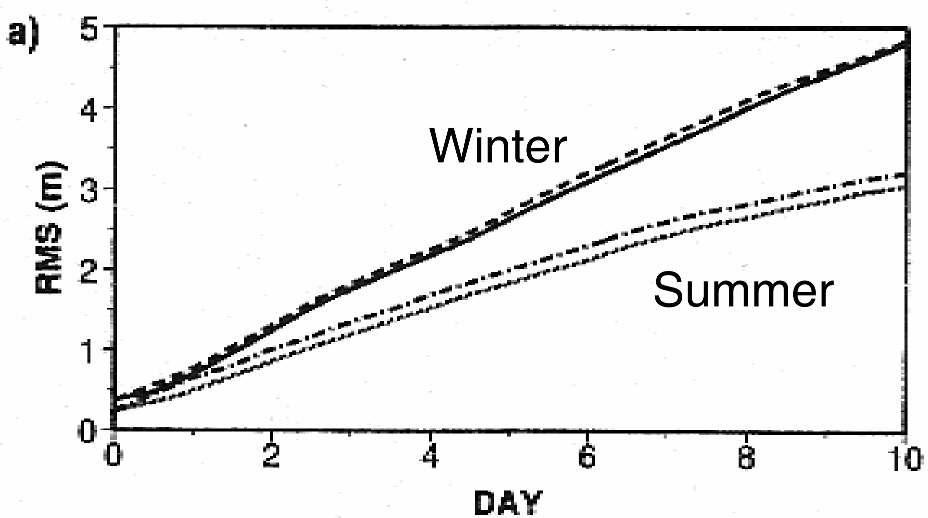
SAMPLING FORECAST ERRORS =
REPRESENTING ERRORS DUE TO USE OF
IMPERFECT MODELS – 2

CURRENT METHODS

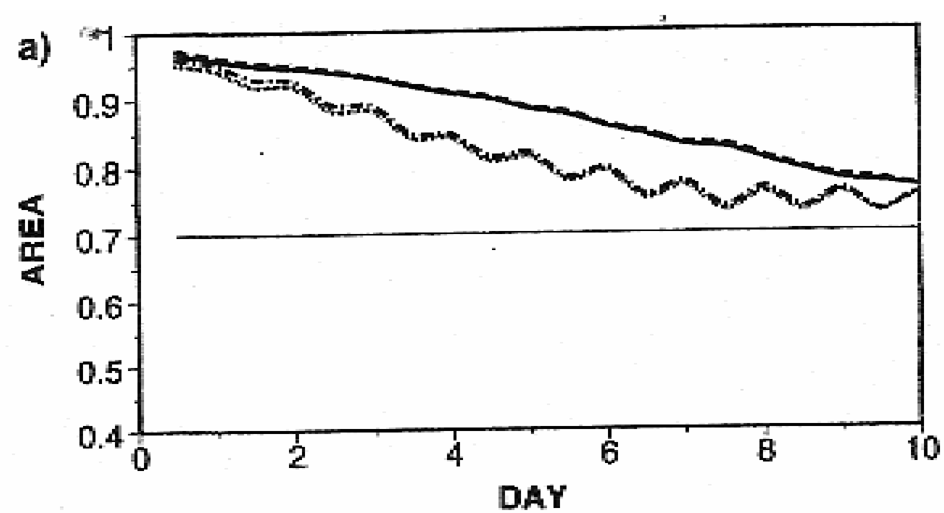
1) Change structure of model (eg, use different convective schemes, etc, MSC)
2) **Add stochastic noise (eg, perturb diabatic forcing, ECMWF)**
   - Modest increase in perturbation growth for tropics
   - Some improvement in ROC skill for precip, for tropics

850 hPa Temp, NH

Spread



ROC Area



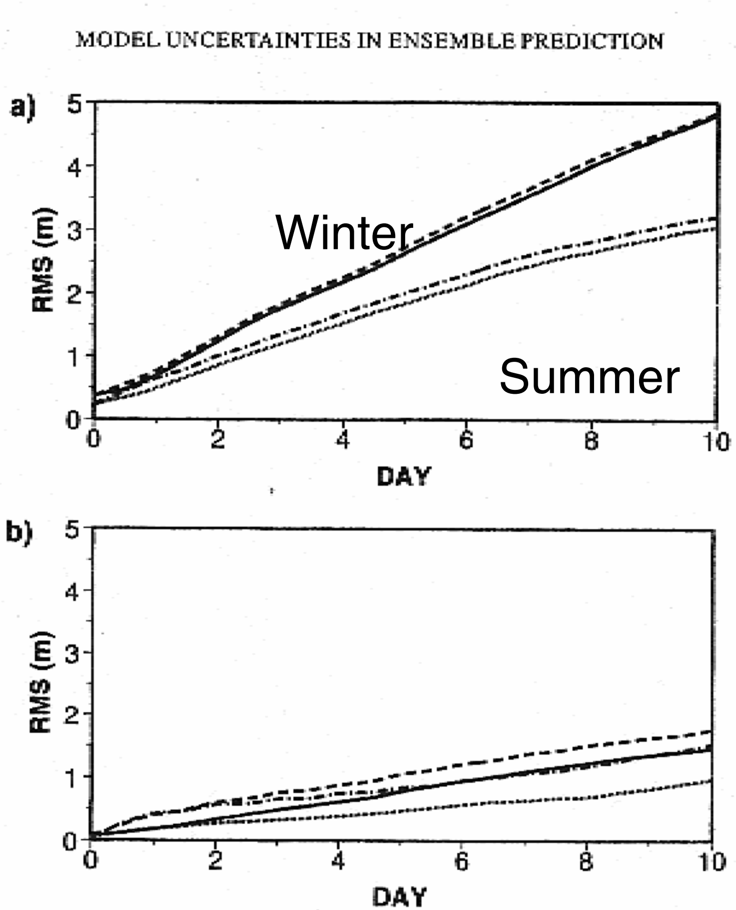
Buizza

Oper vs. Stochastic perturbations

850 hPa Temp

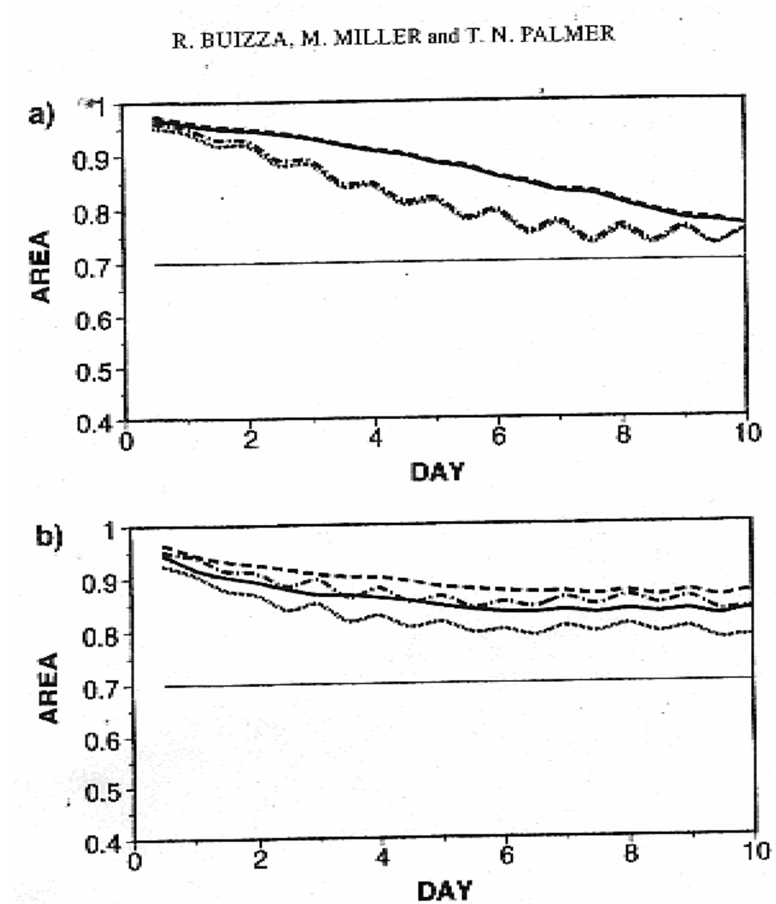
Spread

ROC Area



NH

Tropics



Buizza

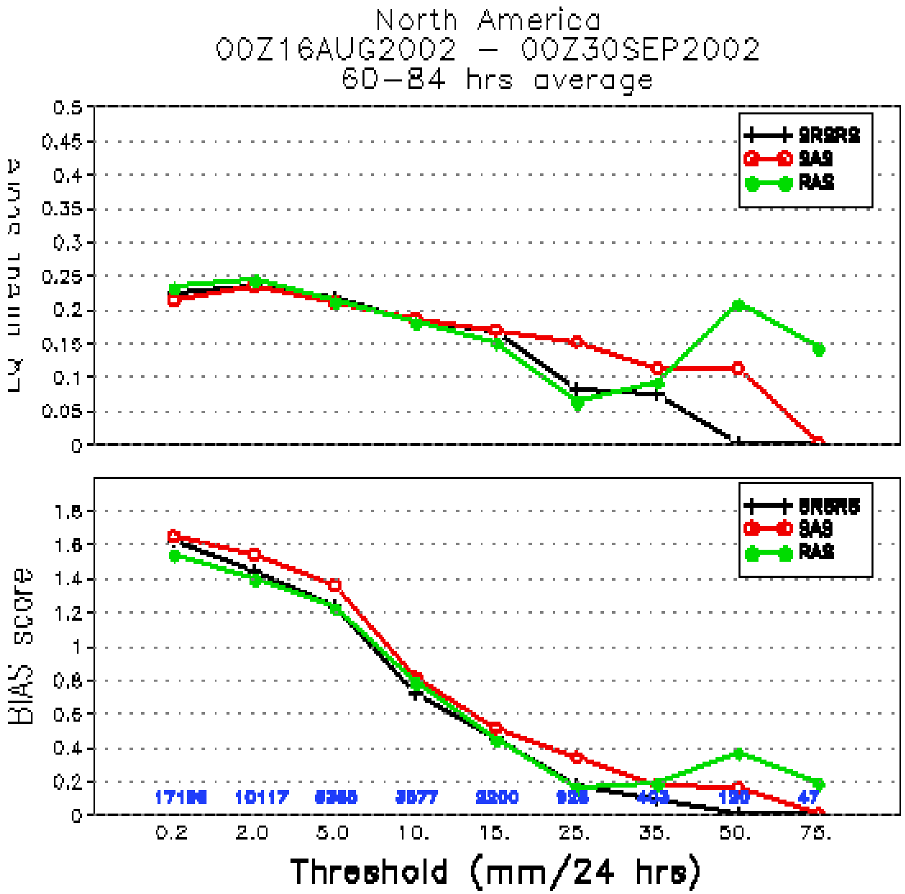
Oper vs. Stochastic perturbations

RESULTS FROM COMBINED USE OF RAS & SAS

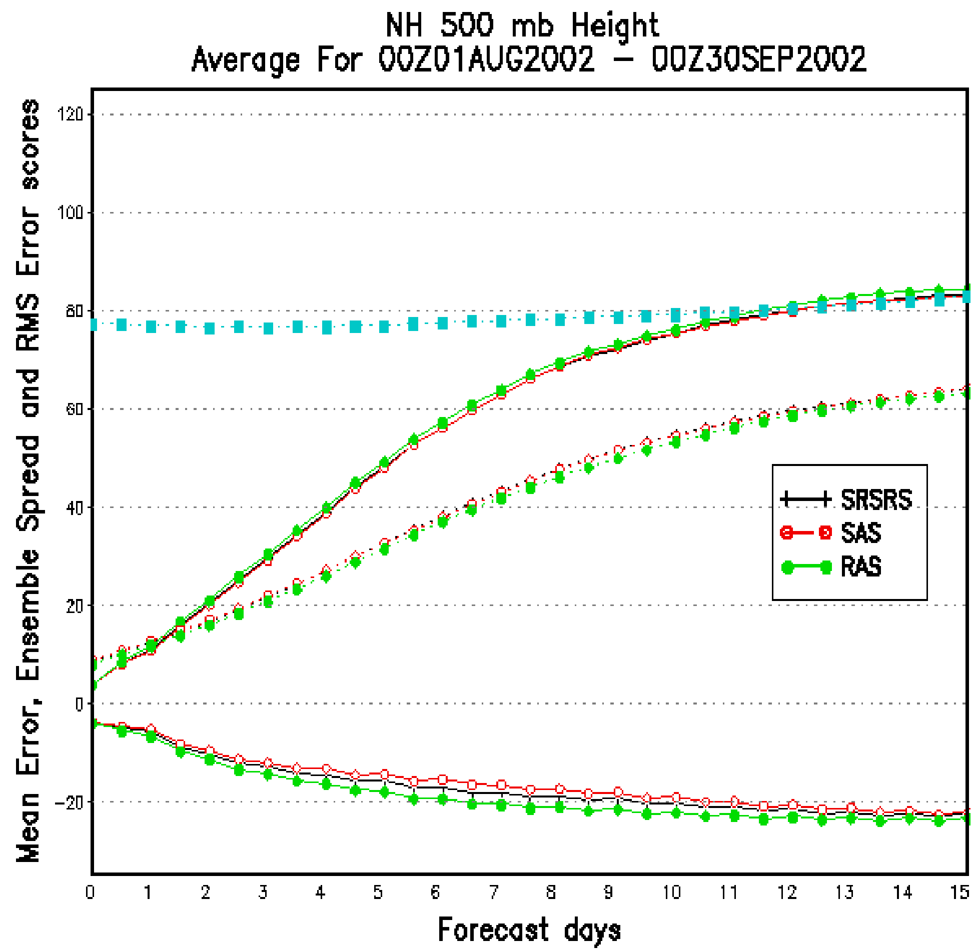
NO POSITIVE EFFECT ON PRECIP OR HEIGHT SCORES

D. Hou

Precipitation Forecast Scores Day 3
SAS, RAS, & Combination



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

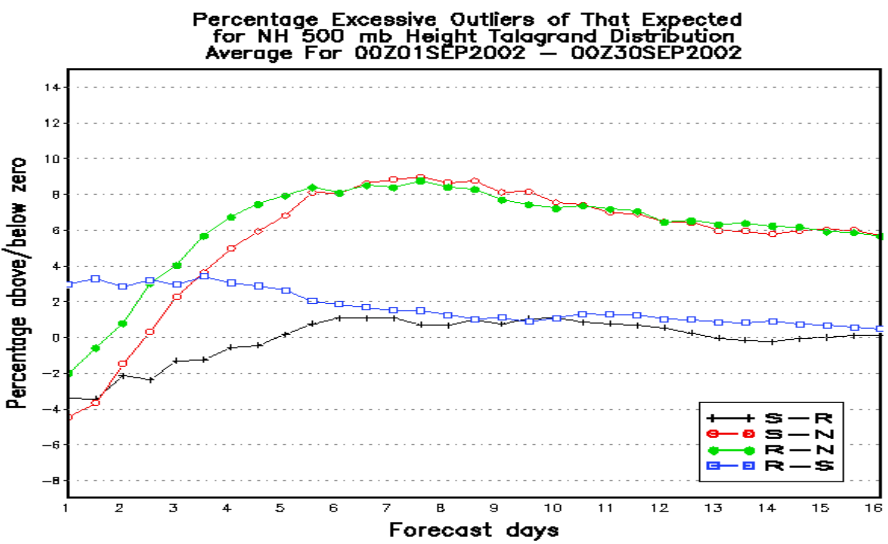


RESULTS FROM COMBINED USE OF RAS & SAS

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

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

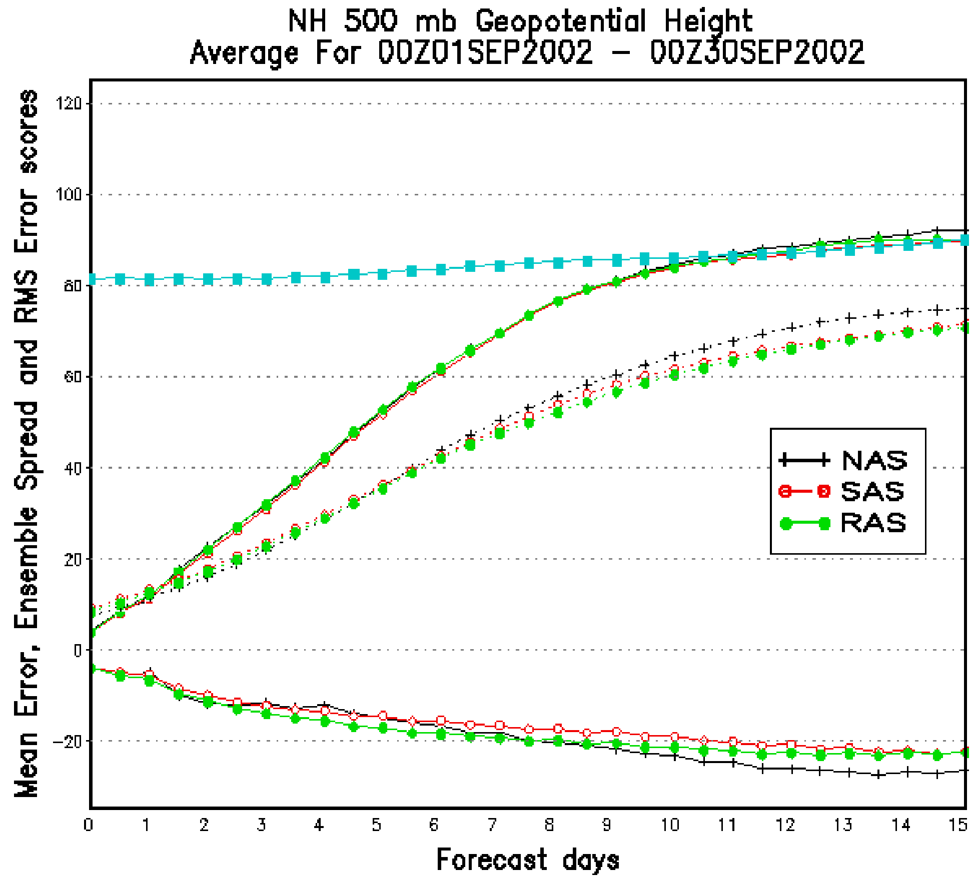
AFTER BIAS CORRECTION, SAS & RAS SUB-ENSEMBLES COVER SAME SUBSPACE



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



STOCHASTIC PERTURBATIONS - PLANS

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

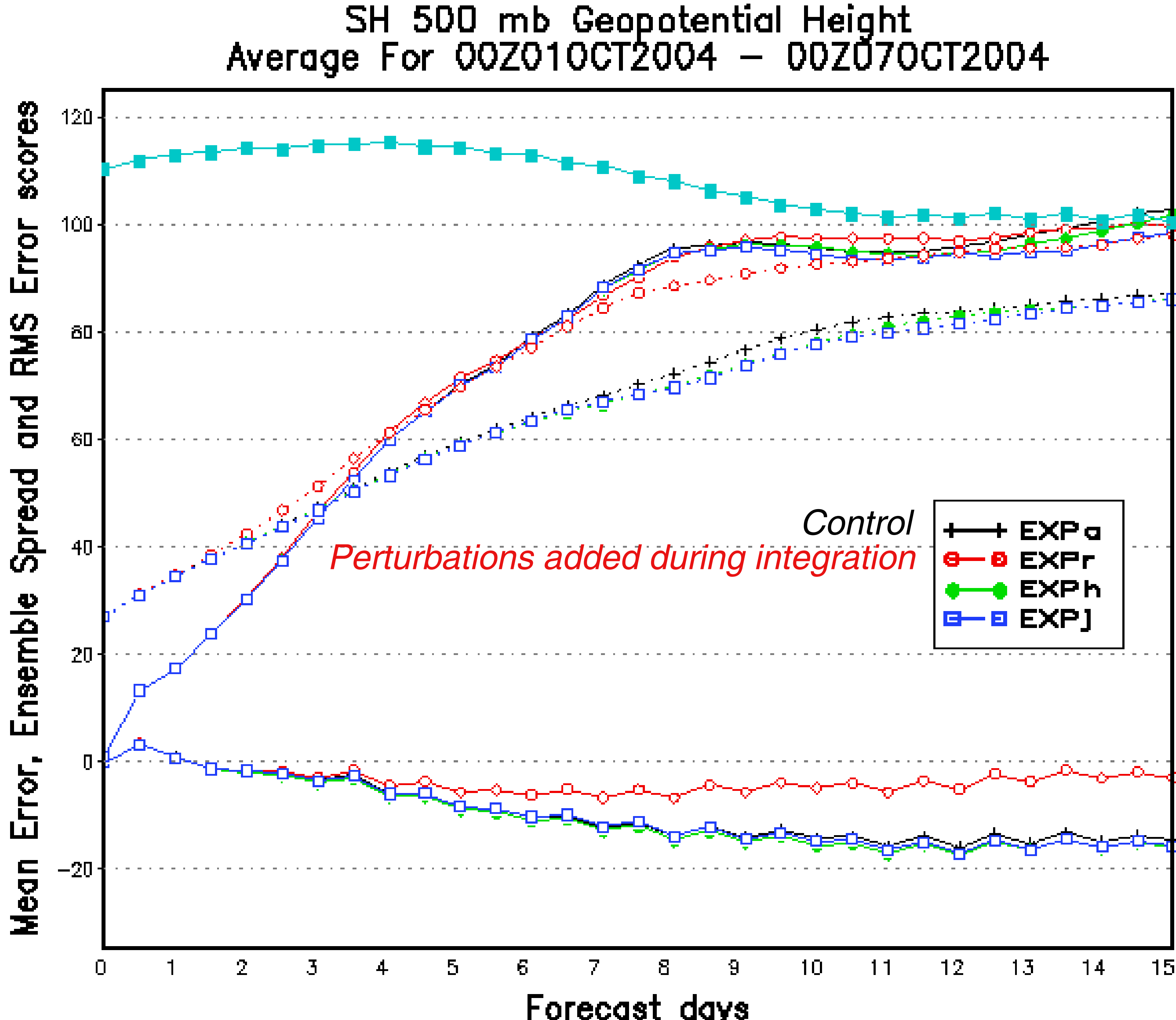
METHOD UNDER DEVELOPMENT (EMC, sponsored by OGP)

- 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)

TO BE TESTED


SH 500 mb Geopotential Height
Average For 00Z01OCT2004 - 00Z07OCT2004
Mean Error, Ensemble Spread and RMS Error scores
Forecast days
Control
Perturbations added during integration
EXPa
EXPr
EXPh
EXPj
120
100
80
60
40
20
0
-20
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15

D. Hou

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	1st 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,

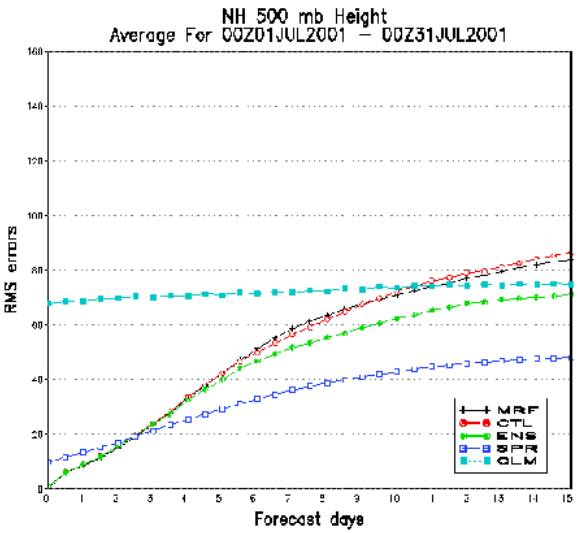
ENSEMBLE OFFERS TOOL TO SEPARATE INITIAL & MODEL ERRORS

Case dependent errors can be captured and corrected

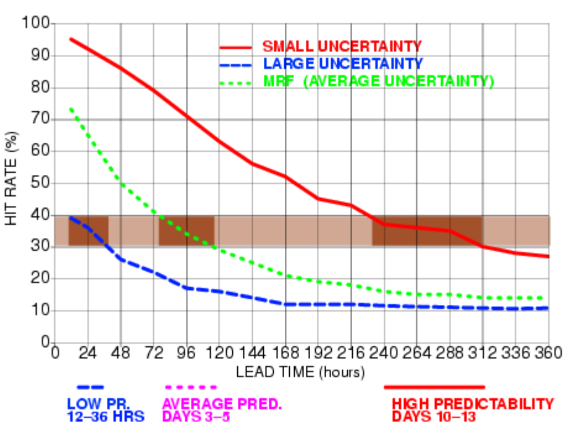
WILL NEW APPROACH ADD VALUE?

WILL IT ENHANCE RESOLUTION OF PROBABILISTIC FCSTS?

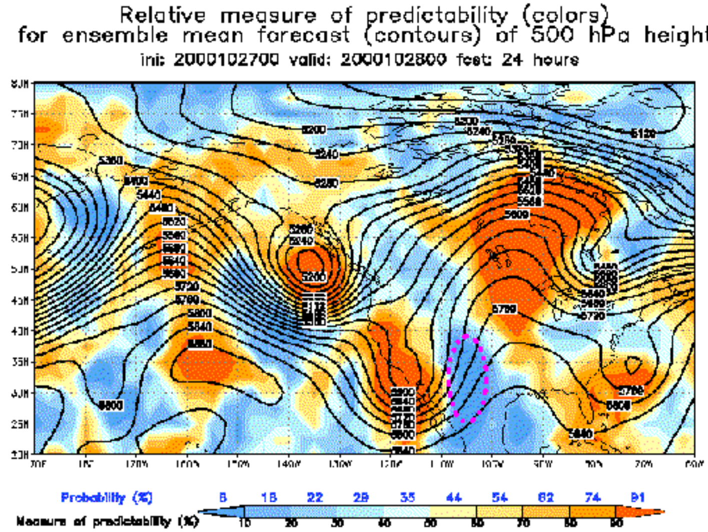
WILL IT GIVE CASE-DEPENDENT ESTIMATES (INSTEAD OF AVERAGE STATISTICAL MEASURE) OF MODEL-RELATED UNCERTAINTY?

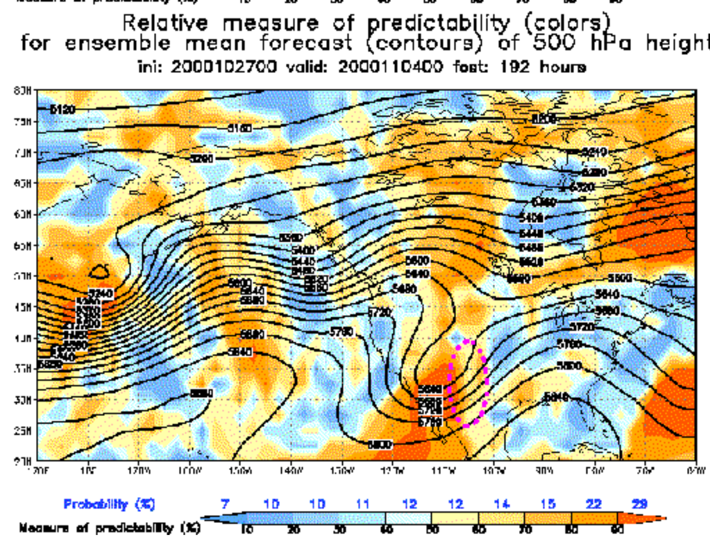


SEPARATING HIGH VS. LOW UNCERTAINTY FCSTS



UNCERTAINTY OF FCSTS CAN BE *QUANTIFIED IN ADVANCE*





SUMMARY

GOALS OF DATA ASSIMILATION

- Record past
- Initialize forecasts

- **LINKS BETWEEN DA & ENSEMBLE FORECASTING**
  – Ensemble describes forecast uncertainty due to dynamics
  – DA combines (ensemble) forecast and observed data

- **DA ISSUES IN ERA OF SATELLITES**
  – More data – Less need to analyze – Challenges remain

- **FORECASTING IN A CHAOTIC ENVIRONMENT**
  – Need to monitor case dependent variations in forecast uncertainty

- **ESTIMATING & SAMPLING INITIAL ERRORS**
  – Bred vectors explain more forecast error variance than other operatnl schemes
  – ET (ensemble-based DA) scheme(s) offers extension of breeding

- **ESTIMATING & SAMPLING MODEL RELATED ERRORS**
  – No universal solution, major challenge for coming years