DATA ASSIMILATION AND ENSEMBLE FORECASTING

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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
• **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?**
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

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**Buizza 2002**

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Ocean/Atm coupled system 5 months 12 months

Initial time Large uncertainty

Day 5 90% Climate probability

Day 12 Almost all predictability is lost – full nonlinear saturation

90% Fcst probability

Mean fcast

x Control fcast

x Climate mean
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 Liouville 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
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\textsuperscript{st}, 2\textsuperscript{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 – Implicit 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 1st & 2nd 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/lowest

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%


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
Ena Prob of Precip Amount Exceeding 0.5 Inch (12.7 mm/day)  Ena Prob of Precip Amount Exceeding 0.5 Inch (12.7 mm/day)
Valid Period: 2000102712–2000102812
Valid Period: 2000110312–2000110412
## COMPARISON OF ECMWF, MSC, AND NCEP ENSEMBLES

<table>
<thead>
<tr>
<th></th>
<th>MSC</th>
<th>ECMWF</th>
<th>NCEP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pj (model uncertainty)</strong></td>
<td>2 models + Diff. Ph. Par.</td>
<td>Pj=P0 (single model)</td>
<td>Pj=P0 (single model)</td>
</tr>
<tr>
<td><strong>dPj (random mod err)</strong></td>
<td>2 models + Diff. Ph. Par.</td>
<td>dPj=r_{j}*Pj (stoch. physics)</td>
<td>dPj=0</td>
</tr>
<tr>
<td><strong>Aj</strong></td>
<td>2 models</td>
<td>Aj=A0 (single model)</td>
<td>Aj=A0 (single model)</td>
</tr>
<tr>
<td><strong>oj (obs error)</strong></td>
<td>Random perturbations</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td><strong>ej (initial uncertainty)</strong></td>
<td>ej from Anal. Cycles</td>
<td>ej=e_{0}+d_{e}(SV)</td>
<td>ej=e_{0}+d_{e}(BV)</td>
</tr>
<tr>
<td><strong>hor-res HRES control</strong></td>
<td>-</td>
<td>-</td>
<td>T170(d0-7)&gt;T126(d7-16)</td>
</tr>
<tr>
<td><strong>hor-res control</strong></td>
<td>TL149</td>
<td>TL255 (d0-10)</td>
<td>T126(d0-3.5)&gt;T62(d3.5-16)</td>
</tr>
<tr>
<td><strong>hor-res pert members</strong></td>
<td>TL149</td>
<td>TL255 (d0-10)</td>
<td>T126(d0-3.5)&gt;T62(d3.5-16)</td>
</tr>
<tr>
<td><strong>vertical levels (c&amp;pf)</strong></td>
<td>23 and 41, 28</td>
<td>40</td>
<td>28</td>
</tr>
<tr>
<td><strong>top of the model</strong></td>
<td>10hPa</td>
<td>10hPa</td>
<td>3hPa</td>
</tr>
<tr>
<td><strong>perturbed members</strong></td>
<td>16</td>
<td>50</td>
<td>10</td>
</tr>
<tr>
<td><strong>forecast length</strong></td>
<td>10 days</td>
<td>10 days</td>
<td>16 days</td>
</tr>
<tr>
<td><strong>daily frequency</strong></td>
<td>00 UTC</td>
<td>12 UTC (00 UTC exp)</td>
<td>00 and 12 UTC</td>
</tr>
<tr>
<td><strong>operational impl.</strong></td>
<td>February 1998</td>
<td>December 1992</td>
<td>December 1992</td>
</tr>
</tbody>
</table>
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 control
  - Poorer (old OI) ensemble analysis
- 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 perturbations and error in control forecast 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
EXPLAINED ERROR VARIANCE AS A FUNCTION OF ENSEMBLE SIZE

METHOD: Compute correlation between ens perturbations and error in control forecast 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

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?
## EXISTING/PROPOSED APPROACHES

### FIRST GENERATION INITIAL PERTURBATION TECHNIQUES

<table>
<thead>
<tr>
<th>ESTIMATION</th>
<th>PERTURBED OBSERVATIONS (MSC, Canada)</th>
<th>BREEDING with Regional Rescaling (NCEP, USA)</th>
<th>SINGULAR VECTORS with Total Energy (ECMWF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESTIMATION</td>
<td>Realistic through sample, case dependent patterns &amp; amplitudes</td>
<td>Fastest growing subspace, case dependent patterns</td>
<td>No explicit estimate, not flow dependent</td>
</tr>
<tr>
<td>SAMPLING</td>
<td>Random for all errors, incl. non-growing, potentially hurting short-range performance</td>
<td>Random in subspace of fastest growing errors; <em>Some dependence among perts.</em></td>
<td>Directed, dynamically fastest growing in future</td>
</tr>
<tr>
<td>CONSISTENCY BETWEEN ENS &amp; DA SYSTEMS</td>
<td>Very good; quality of DA lagging behind 3DVAR?</td>
<td><em>Time-constant variance due to use of fixed mask</em></td>
<td>Poor, potentially hurting short-range performance</td>
</tr>
</tbody>
</table>
## EXISTING/PROPOSED APPROACHES - 2

### SECOND GENERATION INITIAL PERTURBATION TECHNIQUES

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

(a) spread for energy(ET)

(b) ratio of ana/fore spread(ET)

(c) spread for energy(ETKF)

(d) ratio of ana/fore spread(ETKF)

(e) spread for energy(breeding, 6h)

(f) ratio of ana/fore spread(breeding, 6h)

(g) spread for energy(ET breeding, new mask)

(h) ratio of ana/fore spread(ET breeding, new mask)

Rescaling factor distribution

ET

ETKF

Breeding

ET+rescaling

M. Wei et al.
Amp Factor ➔ Effective Dim ➔ Correlation

M. Wei et al.
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 ↔ 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

Talagrand Distribution (NH 500mb Z)
for 00Z01JUN2002–00Z31AUG2002

Bias in second moment
Perturbation growth lags error growth

NH 500 mb Height
Average For 00Z01JUL2001 – 00Z31JUL2001
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

Talagrand diagrams for 500 hPA, northern extratropics

February 2001

24 hour forecasts

144 hour forecasts

48 hour forecasts

168 hour forecasts

72 hour forecasts

192 hour forecasts

96 hour forecasts

216 hour forecasts

120 hour forecasts

240 hour forecasts

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17

categories

(defined by ordered ensemble members)

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

Oper: 3 model versions
Para: More model diversity

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 other. 500 hPa geopotential height, forecasts started at 0000 UTC on April 18, 1994. Note that initial perturbations are larger for the changing 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 changes in model configuration do not result in larger spread. Data are from Table 4 of Houtekamer et al., 1996.
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

MODEL UNCERTAINTIES IN ENSEMBLE PREDICTION

a) 

Winter

Summer

NH

Tropics

R.M. BUizza, M. MILLER and T.N. PALMER

a)

AREA

b)

AREA

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

North America
00Z16AUG2002 – 00Z30SEP2002
60–84 hrs average

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

NH 500 mb Height
Average For 00Z01AUG2002 – 00Z30SEP2002
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

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

NO DIFFERENCE WHETHER CONVECTIVE SCHEME IS USED OR NOT

D. Hou
STOCHASTIC PERTURBATIONS - PLANS

AREA OF ACTIVE RESEARCH
- ECMWF operational (Buizza et al, 1999), A random number (sampled from a uniform distribution) multiplied to the parameterized tendency
- ECMWF research (Shutts and Palmer, 2004), Cellular Automaton Stochastic Backscatter used to determine the perturbation
- 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
Perturbations added during integration

Control

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*

<table>
<thead>
<tr>
<th>OLD</th>
<th>NEW</th>
</tr>
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<tbody>
<tr>
<td><strong>GOAL</strong></td>
<td>1&lt;sup&gt;st&lt;/sup&gt; Moment</td>
</tr>
<tr>
<td><strong>MEASURE</strong></td>
<td>RMS error</td>
</tr>
<tr>
<td><strong>VARIANCE</strong></td>
<td>Ignored / reduced</td>
</tr>
<tr>
<td><strong>NWP MODEL</strong></td>
<td>Search for best configuration</td>
</tr>
</tbody>
</table>
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