OVERVIEW OF PREDICTABILITY RELATED WORK AT NCEP

OUTLINE / SUMMARY

RECENT CHANGES CURRENT CONFIGURATIONRESEARCH / PLANS USAGE NOTES

For

•**GLOBAL ENSEMBLE FORECAST SYSTEM**

- –4 times per day, increased resolution from Dec. 2003
- –North American Ensemble Forecast S ystem

•**REGIONAL ENSEMBLE FORECAST SYSTEM**

–Multiple model v ersions

•**COUPLED OCEAN-ATMOSPHERE FORECAST SYSTEM**

–N e w coupled model, experiments with bred v ectors

•**WINTER STORM RECONNAISSANCE PROGRAM**

- –Operational program to adaptively collect obser v ations
- THORPEX connection similar concept tested in Atlantic Regional Campaign

NCEP GLOBAL ENSEMBLE FORECAST SYSTEM

R. Wobus, Y. Zhu

RECENT UPGRADE (Apr. 2003)

10/50/60% reductionin initial perturbation size over NH/TR/SH

NEW CONFIGURATIONDECEMBER 2003

CURRENT SYSTEM

TROPICAL STORM TRACK ERRORS

T. Marchok

RECENT UPGRADETested for Aug 24 – Sept 30 2002

- 1) Ensemble mean error lower than GFS hires control
- 2) New reduced initial amplitude improves performance
- 3) SH scores greatly improved

3-WAY INTERCOMPARISON: RESEARCHECMWF, MSC, NCEP

Buizza, Houtekamer et al. **LESSONS LEARNT FOR NCEP**

Need for stochastic perturbations

Orthogonalization of perturbtns may help => Growth of spread is too low => Apply ETKF for generating perturbations

USE ETKF FOR RESCALING BRED PERTURBATIONS

ADVANTAGES COMPARED TO

CURRENT REGIONAL RESCALING:

- 1) Effect of actual obs. error/locations considered
- 2) Orthogonalization of initial perturbations
- 3) 6-hr cycling
- 4) Can be further developed into DA scheme

VERTICAL DISTRIBUTION OF TOTAL ENERGY

Reflects combined effect of

- •*Atmospheric instabilities and*
- •*Observation locations/errors*

Wei, based on Bishop & Wang *HORIZONTAL DISTRB. OF WIND*

When ~20 dropsondes considered 7-Case WSR average initial spread Reflects reduced uncertainty in IC

(d) vertical ave analysis/fcst perts for Wind (obs_GL)

0035-0.003-0.0025-0.002-0.0015-0.001-0.0005 0.0005 0.001 0.0015 0.002

(d) vertical ave analysis/fcst perts for Wind (obs GL)

0.001 0.002 0.003 0.004 0.0 0.007-0.006-0.005-0.004-0.003-0.002 0

EXAMPLE WHERE MODEL MAY HAVE FAILED D. Hou, Y. Zhu STOCHASTIC PERTURBATIONS NEEDED TO:

1) Increase growth of spread; 2) Avoid problems like below

Day 6, 2 members

Da

Day 7, overconfidence?

Relative measure of predictability (colors)
for ensemble mean forecast (contours) of 500 hPa height ini: 2003102300 volid: 2003103000 feet: 168 hours

Day 6, 2 members Day 5, several members

Day 7.5, 1 member?

y 6, 2 members **Example 19 and Seat of Day 4**, still large uncertainty

NCEP Ensemble Forecast

PRODUCTS RELATIVE MEASURE OF PREDICTABILITY, GLOBAL Y. Zhu

Relative measure of predictability (colors)
for ensemble mean forecast (contours) of 500 hPa height
ini: 2003110800 valid: 2003111400 foet: 144 houre

PRECIPITATION TYPE, GLOBAL ENSEMBLE
Ensemble Probability Forecast (Initial: 2003110600)
>0.254mm

B. Zhou

SNOWFALL, REGIONAL Winter Weather Experiment

COM Prob 12h-snow > 1" 60H fcst from 09Z 08 NOV 2003
verifying time: 21z, 11/10/2003

CAPE, REGIONAL Severe Storms, Aviation

NORTH AMERICAN ENSEMBLE FORECAST SYSTEM PROJECT

GOALS: Accelerate improvements in operational weather forecasting *through Canadian-US collaboration*

Seamless (across boundary and in time) suite of products *through joint Canadian-US operational ensemble forecast system*

PARTICIPANTS: Meteorological Service of Canada (CMC, MRB) US National Weather Service (NCEP)

PLANNED ACTIVITIES: Ensemble data exchange (June 2004) Research and Dev elopment -*Statistical post-processing* (2003-2007) *-Product development -Verification/Evaluation*

Operational implementation (2004-2008)

POTENTIAL PROJECT EXPANSION / LINKS:

Shared interest with THORPEX goals of *Improvements in operational forecasts International collaboration*Expand bilateral NAEFS in future *Entrain broader research com munity Multi-center / multi-national ensemble system: MOA with Japan Meteorological Agency*

NAEFS - BENEFITSJ.-G. Desmarais et al.

Two independently developed systems combined, using different:

Analysis techniques Initial perturbations Models

Joint ensemble may capture new aspects of forecast uncertainty

Procedures / software can be readily applied on other ensembles:

ECMWFJMAFNMOC, etc

Basis for future multi-center ensemble

Collaborative effort

Broaden research scope - The Enhanced quality Share developmental tasks - The Increased efficiency Seamless operational suite - Enhanced product utility

11 *Framework for future technology infusion (MDL, NOAA Labs, Univs.)*

THORPEX OBJECTIVESINTERNATIONAL PROGRAM

SCIENCE GOAL:

Promote research leading to ne w techniques in:

Observations (Collect data) Data assimilation (Prepare initial cond.) Forecasting (Run numerical model) Socioeconomic Applications (Post-process, add value, apply)

SCIENTIFIC RESEARCH MUST ENABLE SERVICE GOALS

SERVICE GOAL:

Accelerate impro vements in utilit y of 1-14 day forecasts for high impact weather

THORPEX ANSWER:

Develop new paradigm for weather forecasting through Enhanced collaboration:: lnternationally Among different disciplines

Between research & operations

Example: North American Ensemble Forecast System (NAEFS)

BRIDGING THE GAP BETWEEN WEATHER AND CLIMATE

CURRENT NWS PRACTICE

"CLIMATE" ENSEMBLE: $2)$

- 12-months coupled ocean-atm fcsts a)
- Average the SST fcsts b)

FORECAST NinoS.4 SST ANOMALIES

Run AGCM ensemble forced by average SST fcst C)

STRENGTH:

Ensemble approach used both for coupled and AGCM model fcsts for enhancing (weak) signal

SHORTCOMINGS:

- Coupled ensemble (lagged fcst) perturbations not optimal a)
- b) Uncertainty information related to SST fcst is discarded
- Initial condition information from atmosphere not used C)

BRIDGING THE GAP BETWEEN WEATHER AND CLIMATE

PI ANS

$3)$ **POSSIBLE FUTURE SYSTEM:** "WEATHER AND CLIMATE" ENSEMBLE?

COUPLED MODEL ENSEMBLE -

Use dynamically constructed perturbations

- Nonlinear bred perturbations capture dominant ENSO instability a)
- Initial error present in analysis dominated by same instability b)
- Symmetrically placed perturbed fosts provide optimal ensemble C)

AGCM ENSEMBLE - PART OF COUPLED SYSTEM?

- Use ensemble SST fcsts as various boundary scenarios i)
- ii) Single set of AGCM fcsts for all time ranges (D1-climate)

ONE-TIER SYSTEM - If possible, with coupled ocean model

J. Wang et al.

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PREDICTABILITY EXPERIMENTS WITH COUPLED MODEL G. Yuan

EOFs of long model run Simulated ENSO variab.

EOFs of bred vectors Instabilities (at gradients)

Composite of bred vector SST EOF patterns

EOF timeseries of 2 BVs ~3-4 degrees of freedom

NCEP SHORT-RANGE ENSEMBLE FORECAST SYSTEM

(SREF) J. McQueen, J. Du, B. Zhou, B. Ferrier

OPERATIONAL SYSTEM

- •15 Members out to 63 hrs
- •2 versions of ETA & RSM
- •09 & 21 UTC initialization
- \bullet NA domain
- •48 km resolution
- \bullet Bred initial perturbations
- Products (on web):
	- Ens. Mean & spread
	- Spaghetti
	- Probabilities
	- Aviation specific
- •Ongoing training

PLANS

- *More model diversity - 5+2 model versions*
- *4 cycles per day (3&15 UTC)*
- *32 km resolution*
- *New products*
	- *Aviation*
	- *AWIPS*
	- *Winter Weather Exper.*
- •*Transition to WRF*

NCEP SHORT-RANGE ENSEMBLE FORECAST SYSTEM (SREF) J. Du

Parallel SREF Systems (32km)

32km parallel SREF system

- **1. Targeting cases selected** in areas where critical winter weather events with high forecast uncertainty may have a potentially large societal impact.
- **2. Sensitivity calculations** performed using ETKF, and a **decision** is made (flight/no flight).
- **3. Observations** are taken and used in operational analysis and forecast products by major NWP centers.
- **4. Verification** is performed by comparing operational analyses/forecasts including the targeted data with analyses/forecasts excluding the targeted data.

WSR03 EXAMPLE L. Holland, S. Majumdar, J. Moskaitis

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COMPARING SINGLE CONTROL & ENSEMBLE FCSTS

- Expected value: Ensemble mean better than control? $\left(\begin{matrix} 1 \end{matrix} \right)$
- More detailed pdf from ensemble (m vs. 1 members)? 2)
- Case dependent variations in spread: Ensemble has skill? 3)
- Is it only 2nd moment (spread), or further details in ensemble? $4)$

CAN ENSEMBLES SKILLFULLY PREDICT BIMODALITY? WORK IN PROGRESS

Each fcst pdf pattern needs large number of realizations to establish associated distribution of observations

APPROACH:

Use climate pdf as reference (10 climatologically equally likely bins) **Drastically reduce dof** by compositing pdf according to location of max

- Identify bimodal distributions wrt climate pdf $1)$
- Locate local maxima & minima in terms of 10 climate bins $2)$
- Establish frequency of verifying analysis falling in max/min bins 3)

CAN ENSEMBLES SKILL FULLY PREDICT BIMODALITY?

1) Given overall ensemble fcst distribution -

Does bimodality occur more frequently than expected by chance?

Many bimodal pdfs must be due to sampling; have not tested stat, signif

In bimodal fest cases, do obs confirm bimodality? $2)$ **COMPOSITE RESULTS for NH & SH extratr. for Nov 2000–Feb 2001**

EXPECTATION: Verification of bias–reduced fosts will show stronger multimodal behavior

CAN ENSEMBLES SKILLFULLY PREDICT BIMODALITY?

 $4)$ Does multimodality as described here have fcst implications?

CASE STUDY OF LARGE VARIATIONS IN CONSECUTIVE CONTROL FCSTS

USE 50-MEMBER TIME-LAGGED ENSEMBLE

initialized 0909 & 0910 00 &12Z, 0911 00Z

bimodal gridpoints vs a) average # for Sept 2001 (Ratio)

NUMBER OF MULTIMODAL GRIDPOINTS MUCH HIGHER THAN USUAL

Difference in ratio significant? Probably yes (have not checked)

CASE STUDY OF LARGE VARIATIONS IN CONSECUTIVE CONTROL FORECASTS

Distribution of **High-Low MSLP difference**

STRONGLY BIMODAL

Statistically significant? Have not tested

CLUSTER ANALYSIS - Two dominant patterns

CAN CASES LIKE THIS BE IDENTIFIED BY STAT METHODS AS LIKELY REAL?

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•**DEFINITION OF PREDICTABILITY**

–No universall y accepted form?

•**COMPLEX MEASURE OF PREDICTABILITY**

- –W h at is predictable (Probabilistic forecast format)
- –Forecast skill (Resolution)

•**PREDICTING PREDICTABILITY**

- –Practical aspect (Dynamical-statistical error variance prediction)
- –Theoretical aspect (Predictabilit y depends on our ever expanding kno wledge)

•**HOW PREDICTABILITY CAN BE ENHANCED?**

- –Capture flow dependent variations in predictabilit y
- –Use "high resolution" forecast in probability space
- –Consider details in pdf (Bimodality)

•**POSSIBLE FUTURE ENHANCEMENTS**

- **CAPTURE MODEL RELATED FLUCTUATIONS IN FORECAST UNCERTAINTY**
- –Represent model errors due to
	- •**Structural**
	- •Parametric
	- •Closure type uncertainties

NEED (COSTLY AND) COMPREHENSIVE APPROACH?

SUMMARY

PREDICTABILITY (RESOLUTION) IS ENHANCED WHEN

•**Flow dependent fluctuations in uncertainty** captured

•Ensemble mode vs. control forecast

•Stronger effect at longer lead times

•**Detailed** (and not bivariate) **probability distribution** is used

•Stronger effect at shorter lead times

•Only broad features of pdf, or details also matter?

•**Bi- and multimodality** appears to contribute to ensemble skill

NCEP ENSEMBLE REPRESENTS ONLY INITIAL VALUE RELATED UNCERTAINTY

CAN VARIATIONS IN FORECAST UNCERTAINTY DUE TO MODEL IMPERFECTNESS BE ALSO CAPTURED?

WOULD THIS LEAD TO ENHANCED PREDICTABILITY?

•Lower ensemble mean rms error?

•Increased resolution (use of more close to 0 and 100% fcst probability values)?

•Details in pdf more trustworthy?

MODEL RELATED FORECAST UNCERTNAINTY

SOURCES OF UNCERTAINTY -*MODELS ARE IMPERFECT*:

- 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

REPRESENTING MODEL RELATED FORECAST UNCERTAINTY -*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
	- theoreticall

30**LOTS OF WORK, & POTENTIAL?**

WHAT IS PREDICTABILITY?AND FORECASTING?

DISCUSSION AT SEPT. 2002 ECMWF WORKSHOP –

No generally accepted, clear definition?

- •Shukla:
	- Predictabilit y Just talking about things, without reall y doing it, theory
	- Forecasting The REAL thing, telling what's going to happen
- • Palmer:
	- Predictabilit y Has practical aspect, probabilistic forecasting, link with users
- •Webster:
	- Predictabilit y Explore what can be skillfully predicted
- •Simple measures of predictability:
	- Linear –
		- Global or local Lyapunov Vectors/Exponents (LVs)
		- Finite-Time Normal Modes (FTNM, Frederiksen & W ei)
		- Singular vectors (SVs)
	- –Nonlinear -
		- Bred vectors (Nonlinear LVs)
		- Nonlinear SVs, etc

WHAT IS PREDICTABILITY?WHAT IS FORECASTING?

PREDICTABILITY -STUDYING WHAT IS PREDICTABLE

*BASED ON TWO FACTORS***:**

INHERENT NATURE OF FLOW

Theoretical approach – Have to make oversimplifying assumptions (see measures) Provides general information, limited insight

KNOWLEDGE / REPRESENTATION OF

Initial state of system

Laws governing evolution of system

Practical approach – Tell every da **Predictable?**

Expected error?

Forecast uncertainty? =>

PROBABILISTIC FORECASTING

FORECASTING, IN ITS FULL SENSE, IS PROBA BILISTIC, WITH C ASE SPECIFIC PREDICT ABILITY INFORM A TION => *ASSESSMENT OF PREDICTABILITY IS PART OF FORECASTING*

*"NO FORECAST IS COMPLETE UNLESS PROVIDED IN PROBABILISTIC FORMAT"*EXTRA INFORMATION FOR USERS?

"PREDICTING PREDICTABILITY"?

Don't know what organiz ers had in mind…

PRACTICAL INTERPRETATION:

Given **current** probabilit y forecast AND distribution of observing locations at **future** time **Predict how forecast uncertainty will change**

D ynamical-statistical methods

APPLICATION – Targeted observations (Bishop et al., Berliner et al.)

THEORETICAL INTERPRETATION:

Predictability is strongly linked with forecasting and depends on our knowledge of: Initial conditions

Governing equations

Given **current** level of predictabilit y, and expected advances that lead to **future** observing, data assimilation, and forecast systems –

> **Predict ho w predictability will change in 50 (100) years Can't do this – Instead:**

APPROACH: Look at predictability using different existing forecast methods Assess ho w i mpro vements contribute to enhanced predictability Speculate what ad v ances can be expected

*PHILOSOPHICAL ASPECT***–**

PREDICTABILITY DEPENDS ON OUR UNDERSTANDING OF NATURE

HOW TO MEASURE PREDICTABILITY?*USE FORECAST SKILL MEASURES*

Assume perfect reliability – S kill is measured by resolution

CAN BE statistically corrected (assuming stationary processes)

CANNOT be statistically corrected - INTRINSIC VALUE OF FCST SYSTEM

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For perfectl y reliable fcsts, resolution = ensemble spread = spread in observations => **Perfect predictability** = only 0 & 100% probabilities used, and always correct **No predictability** = No matter what we forecast, climate distribution is observed

BRIER SCORE (BS) and BRIER SKILL SCORE (BSS) For verifying categorical probability forecasts (event occurs or not) **VERIFYING ANALYSIS ENSEMBLE MEMBERS** 500 HPA **HEIGHT OBSERVATION** Total of n pairs of cases d N_k cases with p_k probability 80% **FCST PROB** 20% $\overline{d}_k = \frac{1}{N_k} \sum_{i \in N_k} d_i$ P, BS (p, d) = $\frac{1}{n}$ [$\sum_{i=1}^{n}$ (p_i - d_i)²]

$$
BS = \frac{1}{n} \left[\sum_{k=1}^{K} N_k (p_k - \overline{d}_k)^2 \right] - \frac{1}{n} \left[\sum_{k=1}^{K} N_k (\overline{d}_k - \overline{d})^2 \right] + \overline{d} (1 - \overline{d})
$$

\nReliability
\nBSS = 1 - $\frac{BS \text{ (forecast)}$
\nBS (climately)

PROBABILISTIC FORECASTING

Based on SINGLE FORECAST –

One integration with an N WP model, **combined with past v erification statistics**

•Does not contain all forecast information

•Not best estimate for future evolution of system

•*UNCERTAINTY CAPTURED IN TIME AVERAGE SENSE -*

•**NO ESTIM A TE OF CA S E DEPENDENT VARI A TIONS IN FCST UNCERT AINTY**

SCIENTIFIC NEEDS - DESCRIBE FORECAST UNCERTAINTY ARISING DUE TO CHAOS

ORIGIN OF FORECAST UNCERTAINTY

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

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

Chaotic system $+$ Initial error $=$ (Loss of) Predictability

Buizza 2002

INFORMATION CONTENT

Use 10 climatologically equally likely bins to define events

 $Entropy = Plog_2 P_1$

Information in one forecast = $I = 1 - \sum_{i=1}^{10} P_i \log_{10} P_i$

Average info in n independent fcsts = $I_{ave} = \frac{1}{n} \sum_{i=1}^{n} I_i$

Categorical control fest can use only a fixed set of probabilities based on average reliability

Ensemble can differentiate between well and less predictable situations

We assume that forecasts are perfectly reliable (forecast probabilities match observed frequencies)

For control: Use average reliability when fcst falls/ doesn't fall in a climate bin (fixed value)

For ensemble: Use average reliability for bin with most ensemble members (depends on how many fests fell in bin), distribute remaining probabilities equally among rest of bins

INITIAL CONDITION RELATED ERRORS

- *Sample initial errors*
- *Run ensemble of forecasts*
- *Can flow dependent variations in forecast uncertainty be captured?*

• *May be difficult or impossible to reproduce with statistical methods*

Brier Skill Score for the NH extratropics, for March-May 1997. Forecasts are made for 10 climatologically equally likely bins; results shown here are the average for the two extreme bins The bin where the control or ensemble mode falls is assigned a probability corresponding to the observed frequency of the verifying
analysis falling into the same bin (P), while the remaining 9 bins are assigned (1-P)/9 assuming perfect reliabil-
(assuming perfect reliabil-
ity). Note that depending on the value of the mode (1<M<10). the corresponding observed frequenc'y for the ensemble (but not for the control) varies widely.

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 fosts 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**

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).

Relative measure of predictability (colors)
for ensemble mean forecast (contours) of 500 hPa height ini: 2001101100 valid: 2001101700 feet: 144 hours

80) 751 70 656 601 55) so سما 52 351 30) 25 $20M$ Probability (%) Measure of predictability $\langle \mathbf{x} \rangle$

Verification

Relative measure of predictability (colors)
for ensemble mean forecast (contours) of 500 hPa height ini: 2001101600 valid: 2001101700 feet: 24 hours

144 hr forecast

Poorly predictable large scale wave Eastern Pacific – Western US

Highly predictable small scale wave Eastern US

NCEP Ensemble Forecast

ENSEMBLE BASED PROBABILISTIC FORECASTS AND THEIR VERIFICATION

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Brier Skill Score for the NH extratropics, for March-May 1997. Forecasts are made for 10 climatologically equally likely bins; results shown here are the average for the two extreme bins The bin where the control or ensemble mode falls is assigned a probability corresponding to the observed frequency of the verifying
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