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VARIATIONS

Examining the climate system's predictability

by David M. Legler, Director

One of the fundamental tenets motivating CLIVAR is that there is some predictability in the climate system. While the prediction community has successfully demonstrated successful ENSO predictions, there have been some not-so great predictions too. When it comes to producing consistent and skillful forecasts of North American temperature and precipitation at lead times of a season and longer, have we reached the estimated limits of predictability? What are these limits and what processes limit predictability? How should the prediction skill of climate models be calculated and compared?

At the most recent Climate Diagnostics and Prediction Workshop (late October 2006), there were several interesting presentations addressing these important topics. In this issue of

Continued on Page Two

IN THIS ISSUE

Seasonal-to-Interannual Prediction 1
U.S. CLIVAR MJO WG Report 6
New U.S. CLIVAR Leadership.................7
Atlantic Decadal Variability Workshop.......7
Predictability of ENSO 8
Calendar 11

Practices for Seasonal-to-Interannual Climate Prediction

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Accuracy in seasonal-to-interannual climate forecasts for the United States (US) remains a challenge. This despite advances in understanding sources of climate variability and predictability as well as improvements in prediction tools. Our use of the tools has greatly improved in the past decade with the implementation of robust model bias correction and multi-modeling strategies. Furthermore, validation measures have become more sophisticated, rating the performance of forecast systems in a manner more consistent with the probabilistic world they describe. Still, further room for improvement exists. This article outlines the current practices of seasonal-to-interannual climate prediction: current understanding of the sources of variability, the tools used to predict it, common methodologies applied to those tools to produce forecasts, and relevant verification analyses with which to judge the performance of the forecasts. These are forecasts of opportunity, which if used prudently have potential to benefit decision-making.

Background

Before discussing current prediction practices and their accuracies, it is important to distinguish between prediction and predictability itself. The latter is a physical characteristic of the natural system, and is not altered by forecasting methodologies. The tools used to make forecasts are often employed, e.g. judging the model against itself, in determining the theoretical limit of predictability, and as such predictability estimates can indeed change (for non-physical reasons) as models evolve. Nonetheless, it is often of interest to know how the current skill levels differ from the existing theoretical limits because such knowledge guides expectations for the skill impacts of improved practices. However, given the indeterminate nature of predictability estimates, this report focuses on skill estimates obtained by comparing model-derived forecasts with the observed climate, emphasizing seasonal mean surface temperature and precipitation variations over the US.

Attributable causes of US seasonal climate variability

Understanding US seasonal climate variability is essential for exposing the sources of its predictability. Seasonal forecasting (when done at the minimal 15-day lead times beyond which deterministic atmospheric predictions are skillful) is effectively the practice of predicting the climate signal due to external forcings. These forcings include anomalous sea surface temperature (SST), soil moisture, sea ice, and chemical constituents. The resulting climate predictability is known as predictability of the "second kind" arising from the influence of specified boundary conditions on the atmosphere. For seasonal prediction

Continued from Page One

Variations, two Workshop presenters explore predictability. First Ben Kirtman characterizes predictability of ENSO SSTA and then provides an analysis that suggests ocean initial conditions are an important factor for ENSO predictability. Lisa Goddard and Marty Hoerling describe current practices of seasonal-to-interannual climate forecasting and then go on to explore methodologies for verifying and quantifying climate prediction skill in a probabilistic sense for seasonal forecasts.

For longer time scales, the predictability of decadal, multi-decadal, and trend-like climate variations is increasingly recognized as an important research frontier. John Marshall's article reports on a predictability workshop exploring Atlantic region predictability and the elements required for initiating experimental decadal predictions.

Lastly, other articles report on several US CLIVAR activities. The most important of these summarizes the outcomes of the recent (July 2006) US CLIVAR Summit where drought and decadal variability/predictability were recognized to be in need of further coordination.

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practices using fully coupled Earth System models, the notion of such a 2-tiered system with external forcings vanishes, and predictability is of the "first kind" arising solely from the initial Earth System conditions. It is important to note here that for seasonal prediction, longer-term changes of external forcing that are affecting the climate system, especially increasing greenhouse gasses, may be considered constant over the season, although their changes from year to year should probably be included in dynamical models.

We will subsequently examine the skill of forecasts generated from both 1-tier and 2-tier systems. But, for purposes of discussing seasonal predictability, it is helpful to first consider the 2-tier system. The climate responses to the specified external forcings constitutes the "signal", whose probability of occurrence (i.e. verification) depends upon the signal strength relative to seasonal "noise" arising from internal atmospheric variability. Two approaches have been used to estimate such signals, and both focus on the contribution of SST anomalies to seasonal variability. One involves analysis of historically observed SST anomalies and the accompanying global circulation and surface climate impacts. This approach is illustrated in the studies by Barnett (1981), Horel and Wallace (1981), Ward and Folland (1991), Barnston and Smith (1996), to name only a few. An approximately correct atmospheric signal can be identified forced by the ENSO-related SST anomaly pattern, and to a lesser extent by one or two more localized tropical SST patterns (Hastenrath, 1995; Anderson et al. 1999). The period of globally adequate observational analyses is just long enough to resolve differences in the relationships between different "flavors" of ENSO SST forcing and climate over the US (Larkin and Harrison, 2005), but the record is not long enough to robustly connect presently unrecognized non-ENSO-related SST forcings and US climate. In a second approach, atmospheric models are used to simulate US seasonal climate variations during the past half century These find that ENSO SSTA is the primary source of forecast skill related to ocean influences, and that in ENSO's absence skill is largely absent (e.g. Goddard & Dilley 2005; Quan et al. 2006) (Figure 1). Further research is required to better understand the role of non-ENSO ocean states in US climate variability.

Additional open questions concern the signals related to land boundary conditions, sea ice states, and the influence of anomalous atmospheric chemical compositions on US seasonal climate. Especially noteworthy is that no current dynamical practice for seasonal forecasting incorporates the direct effect of anomalous chemical composition, and it is unclear to what extent their implicit effect is already incorporated via ocean states. Among a suite of empirical tools employed by NCEP in their operational seasonal forecasts, the trend of surface temperature has been found to explain a large fraction of US seasonal temperature variations during the past decades (Huang et al. 1996), and this tool explains the majority of US temperature forecast skill at lead times greater than 1 season. Yet, neither the strength, seasonality, nor regionality of such trends have been distinguished from possible transient decadal variations. This leaves open the question on the best practice for including trends and their climatic forcings into seasonal prediction practices.

Current prediction tools and methodologies

The tools used for prediction, as mentioned above, include empirical models and dynamical models. Individually, empirical models continue to be competitive with dynamical models, which attests to the dominance of the linear ENSO signal as the primary skill source over the US. It is not clear if this will continue to be the case if anthropogenically induced changes in the mean state impact the expression of climate variability, such as the teleconnection responses to El Niño conditions in the tropical Pacific or even the expression of ENSO itself. Conversely, the extrapolation of trends by the empirical models has kept pace with the recent increases in the strength and spatial coverage of above-normal temperatures over the US better than the dynam-

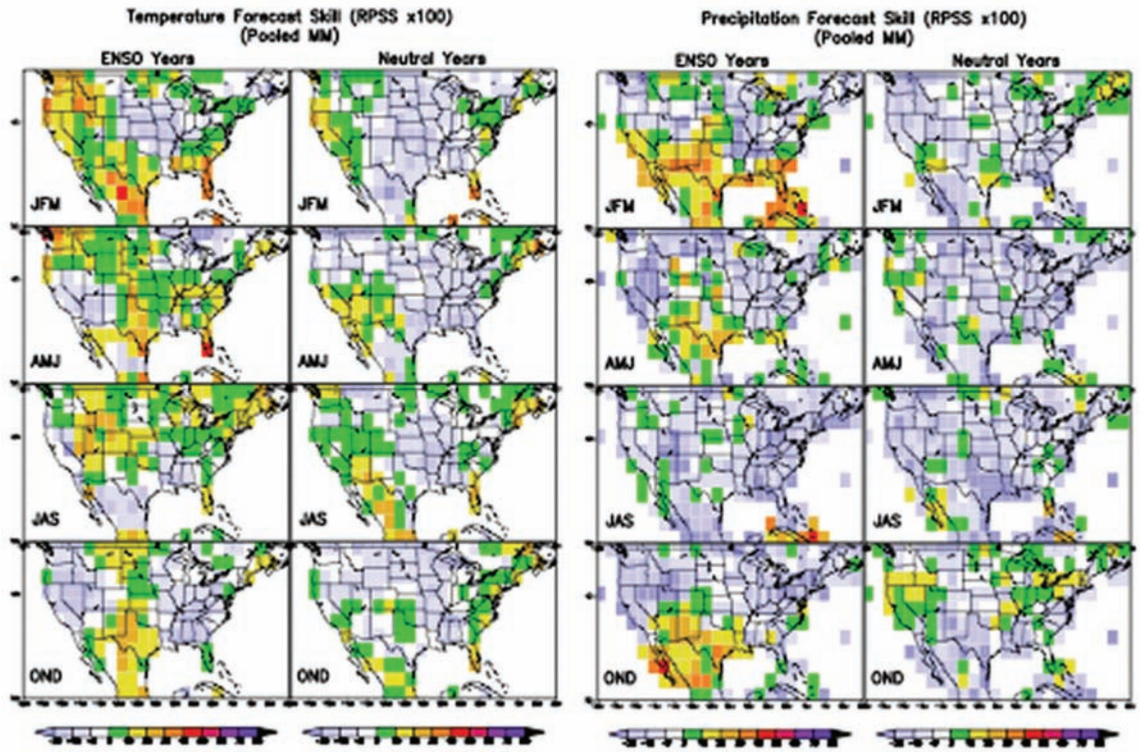

Figure 1 - Differences in skill (RPSS) for 3-category seasonal rainfall multi-model forecasts between ENSO extremes and neutral conditions for the 1950-1995 period. Positive values (green, yellw,red) indicate higher skill during ENSO extremes. (from Goddard and Dilley, 2005)

ical models used for seasonal prediction (not shown). The most notable change in the armory of prediction tools has been the increasing use of coupled general circulation models (CGCMs) over atmospheric general circulation models (AGCMs). In theory CGCMs are superior to AGCMs because the two-way interaction between ocean and atmosphere can proceed realistically; whereas in an AGCM the ocean does not respond to the atmosphere, which leads to unrealistic air-sea heat fluxes over most regions. One exception is the ENSO region (i.e. near-equatorial Pacific) where the ocean largely forces the atmosphere interannually. US seasonal forecast skill obtained with AGCMs is expected to be comparable to that from CGCMs, because the currently realized skill in US terrestrial climate derives primarily from ENSO SSTA, To date, CGCMs still contain substantial biases in their representation of important boundary fields, such as SSTs. As a result, CGCMs currently do not outperform AGCMs. That they have the potential to do so suggests possible future improvements to climate predictions as biases in CGCMs are diagnosed and minimized.

Given the existing biases in prediction tools, considerable effort has gone into methodologies that can identify and reduce them. The simplest of these removes the mean bias of the model climatology, and casts the prediction as anomalies relative to some base period. More complex, though less generalizable methods attempt to spatially correct patterns of anomalous climate due to inadequately resolved topography, or poorly captured teleconnection responses (Landman & Goddard 2002, Tippett et al. 2003). Recently, efforts have focused on attempting to recalibrate the probabilistic response of the model (Doblas-Reyes et al. 2005).

While these methodologies do improve individual model performance, one still finds that some climate signals are captured by some models and not others. This suggests that in addition to sampling the uncertainty arising from imperfect knowledge of initial conditions, the uncertainty arising from imperfect knowledge of the physical processes must also be sampled, specifically those represented through parameterizations. Substantial improvements in overall “predictionability” have been achieved through the combination of several models, so called multi-model ensembling (e.g. Robertson et al. 2004). As will be shown below, since all models do not always share the same strengths and weaknesses, by combining them into a single probabilistic forecast the spatial coverage of positive skill increases, and negative skill is reduced. This improvement in skill has been shown explicitly to result from the increase in model number rather than just the increase in realizations (Palmer et al. 2000). Another important result of multi-model ensembling is the dramatic improvement in the reliability in probabilistic forecasts.

One implicit criterion for combining multiple models is that they all perform ‘adequately’. If one model were found to be measurably worse than the others, it should be dropped. In some cases, the combination algorithm considers past performance of the models, assigning weights accordingly (Rajagopalan et al. 2001). Unfortunately performance weighting requires long histories (40+ years) of model forecasts in order to determine relative model performance robustly. This becomes a problem for

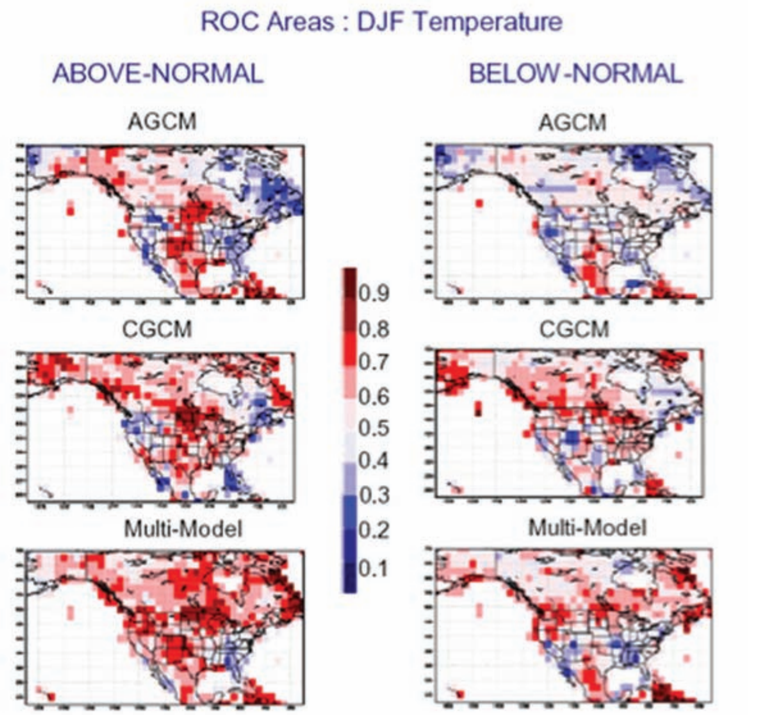

Figure 2. . ROC areas for DJF temperature forecasts at 1-month lead for the period 1981-2001. The AGCM was forced by predicted SSTs. The multi-model forecast is based on equal weighting of 3-category proba-

most CGCMs used for seasonal prediction because the observational data required for their initialization does not exist prior to the 1980s. With only 20+ years of retrospective forecast data, it becomes difficult to assign meaningful weights to individual models. Methodologies for synthetically extending a retrospective forecast history or for combining models that could circumvent the limited model history and still allow for performance weighting could greatly improve the skill of the resulting forecasts.

Forecast system validation

Several measures of forecast validation exist, sometimes giving a different picture of where, when, and which prediction practice yields the most accurate forecasts. In general the use of more than one measure of validation is desirable, and in Figure 1 we have already shown skill based on the rank probability skill score. In this section we highlight additional measures that provide valuable information about US prediction skill. The first is the area under the relative operating characteristic (ROC) curve. For a particular grid point or region, these curves indicate the percentage of hits and false alarms yielded by the forecast system for a given event (e.g. above-normal tercile category), under varying levels of confidence in the forecast. If the event were perfectly predictable by the forecast system, it would have a hit rate of 1.0 and no false alarms. The area under the curve would be 1.0. If the system were unable to distinguish between a hit and a false alarm, those rates would be equal, and the area under the curve would be 0.5, which is considered the level of no skill. Negative skill is indicated by values less than 0.5. What is particularly useful about ROC areas is that they can indicate condition skill, for instance, higher hit rates for the upper tercile category than the lower one. An example is shown in Figure 2, which illustrates that forecasts of above-normal temperature have witnessed higher skill than below-normal temperatures for the Dec-Jan-Feb season during the 1981-2001 period. Figure 2 also illustrates some of the other points raised in the previous section regarding AGCMs, CGCMs and multi-model ensembles. In particular, there is little difference in skill of the AGCM versus CGCM practices, and the multi-model combination of all dynamical systems exhibits the greatest skill.

The second validation diagnostic of forecast performance we demonstrate is reliability. This measure is particularly important as it indicates the extent to which forecast probabilities mean what they say. A striking characteristic of all dynamical models is that their probability forecasts are over-confident (Figure 3). There is no distinction between AGCMs and CGCMs in this shortcoming. Some improvement can be achieved by recalibrating the probability distributions of the individual models (not shown). The greatest improvements are obtained by combining the models, here accomplished by simply averaging the 3-category probabilities of the 8 CGCMs and the 3 AGCMs. There is a negative consequence of such a process, namely that the sharpness of the resulting forecasts is reduced (i.e., fewer high probability forecasts are indicated). Ideally, one wishes to retain as sharp as possible a forecast while ensuring reliability. Work continues towards this goal.

Outstanding questions and room for improvement

What are core activities for improving climate forecasting practices? Developing new models of the atmosphere-ocean-cryosphere-land system, ensuring sustained long term observations, enhancing data assimilation techniques, and improving understanding of seasonal climate variability are essential. A commonly used metric for measuring the impact of such activities is the skill and reliability of forecasts. In this report the skill attributes of existing and emerging dynamical methods of seasonal predictions have been examined.

A relevant question concerns whether U.S. seasonal prediction skill is advancing with newer generation models. Considerable investment has been devoted towards improving climate models, in part for the purpose of advancing seasonal predictions. Recent examples include new efforts to implement an updated global coupled forecast system with increased resolution and improved atmospheric and oceanic components at NCEP (to be called the Coupled Forecast System (CFS03)), with similar efforts underway at NASA/GMAO including their plan to use a global 1° resolution atmospheric model. An implicit assumption behind such efforts is that newer generation dynamical models will lead to improved skill. We know, for example, that predictability exists in the extra-tropical climate that the current generation of models are not realizing (Anderson et al. 1999). Analogies may also be drawn from weather forecasting experience where steady improvements in models and data assimilation techniques resulted in progressively improved weather predictions. It may be that the seasonal prediction models are presently neglecting some important external forcings, such as the increasing greenhouse gasses in the atmosphere, which can affect the characterization (and bias corrections) of the model climate over periods of years. Poorly represented interactions of the atmosphere with the land surface and with the cryosphere may also hamper the skill of seasonal predictions over the US. Another aspect of the climate system that is typically not well represented in the seasonal prediction models is the interaction between the stratosphere and troposphere (Baldwin and Dunkerton, 1999), which has demonstrated occasions of predictable evolution and subsequent influence on the terrestrial climate over the northern mid-latitudes. Even if the model development improves simulations of seasonal climate variability, seasonal prediction skill will nonetheless be limited by inherent signal-to-noise considerations. The relevant question becomes whether the new generation of dynamical models yield signal-to-noise ratios that more accurately reproduce those in nature. It is therefore important to continually document and analyze the seasonal prediction skill from the improved dynamical prediction systems, and to cast those performances within improved knowledge of predictability limits.

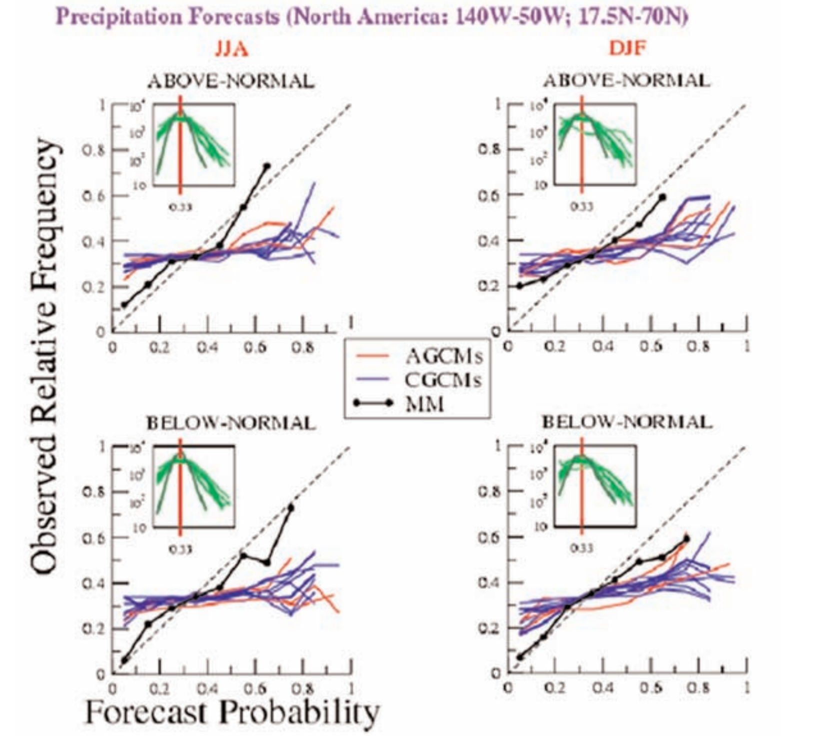

Figure 3. Reliability diagrams for the upper (Above-Normal) and lower (Below-Normal) category of 3-category forecasts for all terrestrial grid points over North America (140W-50W; 17.5N-70N). The colored lines show the reliability of the individual models; the light green lines in the inset boxes show the frequency with which forecasts of a certain confidence were issued for that category. The black line shows the reliability for the multi-model forecast, and the dark green line in the inset graph shows the confidence frequency.

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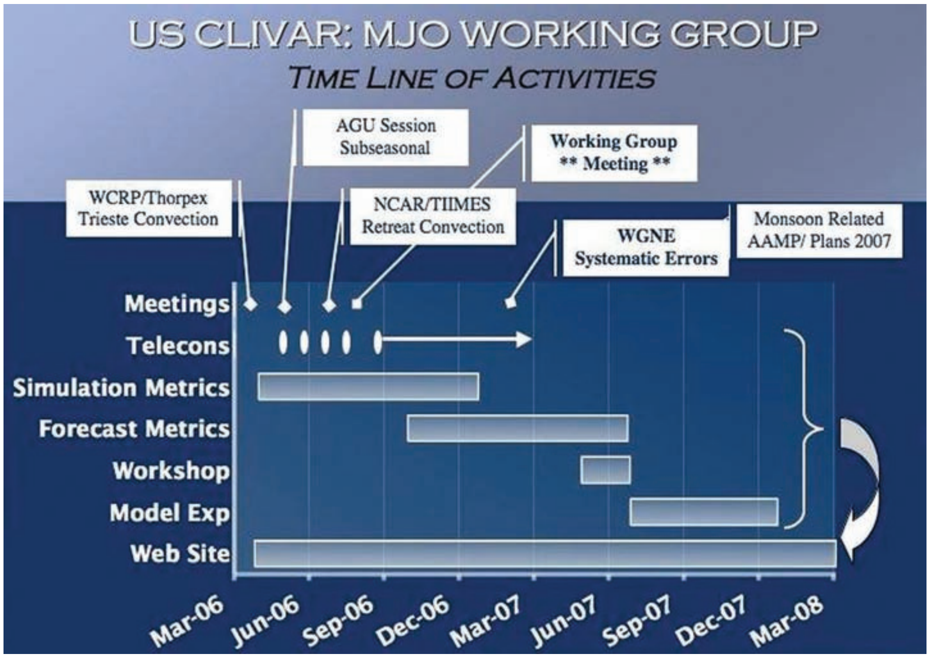
U.S. CLIVAR Madden-Julian Oscillation (MJO)Working Group

Meeting Summary

Duane Waliser, NASA Jet Propulsion Laboratory
Ken Sperber, Lawrence Livermore National Laboratory

In July 2006, the U.S. CLIVAR Madden-Julian Oscillation (MJO) Working Group (MJOWG) held its first working group (WG) meeting in association with the U.S. CLIVAR Summit in Breckenridge, CO. The first meeting followed up on a series of monthly telecons in which the objectives of the WG were discussed and agreed upon. In addition, the website associated with the group's activities was formulated and developed:

(http://www.usclivar.org/Organization/MJO_WG.html), and substantial headway was made in regards to one of the chief goals of the WG, namely, the formulation of MJO metrics that can be applied to model simulation assessments of the MJO. The one and a half day meeting was attended by six of the ten WG members Maloney, Moncrieff, Sperber, Waliser, Weickmann, and Zhang), two substitute members (Higgins for Wang, Stern for Donner), and two international participants (Hendon and Woolnough).



The workshop agenda was largely devoted to the further development and refinement of a set of metrics for validating climate model simulations of the MJO. In addition, there was discussion of metrics for MJO forecasts, follow-on objectives for the WG in terms of model experimentation, future workshops and/or WG meetings. The workshop also provided a venue for the participants to become more familiar with how the applications community views prediction/simulation of the MJO. To this end, two formal presentations were given (both posted on the MJOWG web site). The first presentation was given by W. Higgins on the Climate Prediction Center's (NCEP/NOAA) Experimental Global Benefits and Hazards Assessment, particularly in regards to the role the MJO plays in this assessment. The second was by Andrea Ray on Applications at the Climate-Weather Interface that included discussions on potential users and applications of subseasonal forecast information, particularly in relation to the US and NOAA's Regional Integrated Sciences and Assessments (RISA) program.

To summarize the efforts of the MJOWG, the figure below provides a summary to date of the past and future activities. Notable was the momentum the WG received from a number of recently held meetings. These included the: 1) WCRP/THORPEX meeting on the MJO and Tropical Convection in Trieste, Italy in March, 2006, 2) the AGU session on subseasonal variability in Baltimore in May, 2006, and the NCAR/TIIMES Retreat on Convection in Boulder in July, 2006. Expectations for the future are that the metrics for the assessment of model simulations of the MJO will be completed late in 2006, with the discussion and development of metrics for model forecasts of the MJO being a primary activity in late 2006 and early 2007. The MJOWG intends to post onto the MJOWG web site the metric calculations as applied to the observations in the form of both the data and graphs/maps (and possibly sample code for the more complex metrics), as well as their application to a small set of model simulations. Subsequent to the development of the metrics, the WG will hold a second meeting to discuss plans for specific model simulation and/or forecast experimentation that would form the basis for a workshop in late 2007 or early 2008. The proposed theme for the workshop is "New Thinking, Tools and Resources for Assessing and Improving the MJO". The workshop would stress: 1) new thinking, in terms of: multi-scale structure of the MJO, emphasis on its vertical structure, utility of the forecast framework for model diagnosis, and the weather-climate interface, and 2) new tools and resources, in terms of the wide range of new satellite data, in-situ resources (e.g., GOOS, Indian Ocean Array), and multi-scale modeling approaches (e.g., MMF, large-scale/global CRMs) that have become available/feasible. For continued updates of the activities and plans of the MJOWG, please visit the MJOWG web site.■

New U.S. CLIVAR Chair

by David M. Legler

The end of 2006 marks the end of an era as Bob Weller (below left), chair of the U.S. CLIVAR Committee, takes a well-deserved rest as chair of U.S. CLIVAR. Bob served on the U.S. CLIVAR SSC since its inception (~1999), and has been its co-chair/chair for the past 5 years (starting in 2001). Despite his numerous obligations to lead scientific cruises and serve on other panels, committees, and study groups, Bob could be counted on to always be out front pushing U.S. CLIVAR forward within the scientific and programmatic communities. Bob - we will miss your spirit and positive can-do attitude - job well done!

I'm excited to be able to introduce Marty Hoerling (below right) who has agreed to serve as the new U.S. CLIVAR Chair effective at the beginning of 2007. Marty's expertise and interest in global climate changes and their prediction and attribution bodes well for U.S. CLIVAR. Although Marty does not relish cruising to remote parts of the ocean, I am confident that under his leadership we'll take exciting voyages through some interesting places!

Atlantic Decadal Predictability Workshop Summary

John Marshall
Massachusetts Institute of Technology

Observations are showing that major shifts in regional climate in the Atlantic sector have occurred on time scales as short as decades, and are likely impacting hurricane activity, droughts, sea ice, rainfall, the Arctic and ecosystems. The investments the community has made in paleoclimate research, climate dynamics, climate modeling, and observing systems are providing the tools needed to better understand and ultimately predict such shifts.

A workshop was held at GFDL in June, 2006, to explore community interest in the development of an experimental decadal prediction capability with an Atlantic focus. Some 25 researchers actively involved in decadal variability and predictability came together for a 2-day meeting.

The goals of the workshop were to:

a. Summarize aspects of what is known about decadal Atlantic variability, both in terms of observational analyses and physical mechanisms

b. Discuss and assess what might potentially be predictable

c. Discuss strategies for initializing models for decadal prediction

d. Initiate efforts to catalyze US research on Atlantic predictability and predictions.

Workshop presentations

Workshop presentations addressed the degree to which observed Atlantic decadal and longer fluctuations are anthropogenically forced; decadal-scale fluctuations in Gulf Stream circulation characteristics, and their climatic relevance; the influence of Atlantic SST changes associated with the Atlantic Multi-decadal Oscillation (AMO) versus remote ocean basins on regional Atlantic and North American climate fluctuations; (*continued on page 11)*

The Predictability of ENSO

Ben Kirtman
George Mason University and the Center for Ocean Land Atmosphere Studies

There is currently a debate regarding the processes that ultimately limit the predictability of the El Niño-Southern Oscillation (ENSO). According to this debate, ENSO may be in one of three regimes. In first regime, ENSO is intrinsically chaotic due to the non-linear dynamics of the coupled system. The loss of predictability is primarily due to the uncertainty in the initial conditions. In the second regime, ENSO is self-sustained (due to weak non-linearity) and is periodic, i.e., perfectly predictable. The irregularity of ENSO is due to external weather noise and the loss of predictability is primarily due to this external stochastic forcing. In the third regime, ENSO is damped and stochastically forced by external weather noise. The non-normality of the coupled system allows for limited time super-exponential perturbation growth, and the predictability is limited by the stochastic forcing exciting these optimally growing modes or how efficiently initial condition errors project onto the optimally growing modes. Put simply, the current debate is that ENSO predictability is either limited by initial condition uncertainty or uncertainty as the forecast evolves (i.e., weather noise).

The limit of ENSO predictability is highly dependent on which regime is correct. For example, in the damped regime, the limit of predictability is on the order of 9-15 months, whereas in the chaotic regime the limit is considerably longer (15-24 months). In the self-sustained and stochastically forced regime ENSO appears to vacillates between highly predictable regimes (oscillatory and self-sustained) and periods of low predictability when the variability is driven by the noise. In this case, whether ENSO resides in the predictable or the unpredictable regime is determined by low frequency variability in the background state. Conversely, in the damped regime the background state changes are merely a sampling issue and changes in predictability are associated with how the stochastic forcing projects onto the optimally growing modes. In this case, variations in predictability are a random walk process.

Here we show an example using a relatively simple model of ENSO how the system can vacillate from highly predictable epochs to periods of relatively low predictability. Figure 1 shows the evolution of Nino3.4 SST from a coupled model of ENSO for two different epochs (red curve). These periods were chosen from a long simulation of the model. The dashed green curves show predictability calculations where we have assumed no initial condition error, but there is uncertainty as the forecast evolves. The "forecast (green curves)" and "observations (red curves)" have different weather noise. How closely the green curves track the red curves indicates the limit of predictability. Although not shown here, this can be quantified by calculating the correlation and the root mean square error. By visual inspection of Fig. 1, it is clear that there is much less predictability in the upper panel relative to the lower panel. The point to emphasize with Fig. 1 is that predictability is limited by uncertainty as the forecast evolves (i.e., weather noise) without initial condition error.

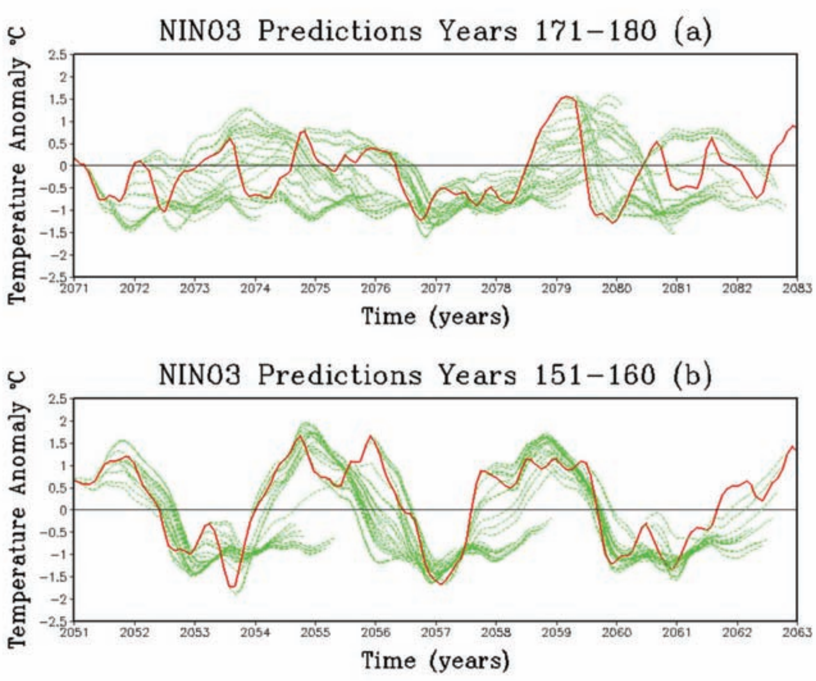


Figure 1. Evolution of the Nino3.4 SSTA from the simulation (red curve) and from the predictability experiments (green dotted lines). The predictability experiments and the simulation have different weather noise realizations. The initial conditions for the predictability calculations are identical to the simulation.

Figure 2. NOAA Coupled Forecast System (CFS) predictability calculations. The solid curves show the root mean square error and the dashed curves show the ensemble forecast root mean square spread. The predictability calculation is based on using one ensemble member at the "truth" for verification. The blue curves in both A and B are the same and indicated the predictability assuming no initial condition error and much reduced weather noise as the forecast evolves. The yellow curves in A show the predictability assuming both initial condition uncertainty and uncertainty as the forecast evolves. The yellow curves in B show the predictability assuming no initial condition uncertainty, but continued weather noise as the forecast evolves.

Even with perfect initial conditions there will be periods (upper panel) where predictability is relatively low (i.e., early 1990s) and periods where predictability is relatively high (i.e., 1980s). Part of the debate is whether the predictable and unpredictable periods are, in fact, themselves predictable.

It is important to note that all of our estimates of ENSO predictability are model-based estimates and that model error significantly impacts these estimates. For example, if the model of ENSO is a simple sine wave, then estimates of predictability would indicate that ENSO is perfectly predictable. We know this is not the case. On the other hand, if the model of ENSO is persistence, then we expect that the estimates of the limit of predictability would be much too short. In other words, we cannot ignore the impact of model error on the estimates of the limit of predictability, and this is why model fidelity and actual prediction skill assessments need to be married to predictability studies. The simple model results noted above are very useful for understanding and formulating hypotheses, but these ideas must be tested in models that have realistic ENSO variability and produce credible ENSO predictions

Predictability Using Coupled Models.

From the perspective of making ENSO predictions with state-of-the-art coupled general circulation models (CGCMs), it is not obvious whether it matters which regime is correct. Presumably, the CGCMs include the possibility of all three regimes. However, in terms of improving predictions and realizing predictability, we need to quantify the mechanisms than limit predictability in CGCMs. Here we show results from the new NOAA coupled forecast system (CFS).

The NOAA CFS coupled model is among the best in world in terms of ENSO prediction. In the example shown here, we diagnose how both initial condition uncertainty and uncertainty as the forecast evolves impacts the estimate of the limit of predictability. Figures 2A and 2B show the Nino3.4 SST root mean square (rms) error for a set of predictability calculations with CFS. The rms spread of the ensemble is also shown in Figure 2. Both the spread and the error are reasonable metrics for estimating the limit of predictability and closely track one another here. The predictability calculation is based on the ensemble CFS forecasts where we have used one of the ensemble members to represent the "truth." In order to reduce the impact of weather noise as the forecast evolves, we have applied the interactive ensemble coupling strategy to the CFS and have performed a sequence of prediction experiments that mimic the CFS control forecast. The interactive ensemble coupling strategy uses an ensemble of atmospheric model realizations coupled to a single ocean model realization. The atmospheric realizations only differ by small perturbations in the initial conditions. Ensemble averaging is applied to the air-sea fluxes felt by the ocean model thereby reducing the effect of atmospheric noise on the ocean. Each atmospheric realization feels the same SST produced by the ocean component. Relatively large values of the rms error (Figure 2) indicate that predictability is lost. The yellow rms error curve in Figure 2A corresponds to

Calendar of CLIVAR and CLIVAR-related meetings

Further details are available on the U.S. CLIVAR and International CLIVAR web sites: www.usclivar.org and www.clivar.org

The Humboldt Current System: Climate, ocean dynamics, ecosystem processes, and fisheries
27 November-1 December 2006
Lima, Peru
Attendance: Open
Contact: http://irdal.ird.fr/hcs-conference.imarpe.fao.ird.php3

GSOP-II Meeting
8-9 December 2006
La Jolla, California
Attendance: Invited
Contact: www.clivar.org

AGU Fall Meeting
11-15 December 2006
San Francisco, California
Attendance: Open
Contact: www.agu.org

U.S. CLIVAR Predictability, Predictions and Applications Interface Panel Meeting
14 December 2006
San Francisco, California
Attendance: Invited
Contact: www.usclivar.org

Meridional Overturning Circulation Observational Meeting
10-12 January 2007
Miami, Florida
Attendance: Open
Contact: www.ametsoc.org

AMS Annual Meeting
14-18 January 2007
San Antonio, Texas
Attendance: Invited
Contact: Chris Meinen (NOAA AOML)

The Workshop on Monsoon Climate Variability and Change, and Their Impacts on Water, Food, and Health in Western India
5-7 February 2007
Ahmedabad, Gujarat India
Attendance: Open
Contact: http://www.decvar.org/workshops_conferences.php

3rd WGNE Workshop on Systematic Errors in Climate and NWP Models
12-16 February 2007
San Francisco, California
Attendance: Open
Contact: http://www-pcmdi.llnl.gov/wgne2007

SOLAS Open Science Conference
6-9 March 2007
Xiamen Province, China
Attendance: Open
Contact: http://www.solas2007.confmanager.com/main.cfm?cid=457

CEOP Implementation Planning Meeting
12-14 March 2007
Washington, DC
Attendance: Open
Contact: http://www.gewex.org

4th International CLIVAR Climate of the 20th Century workshop
13-15 March 2007
Exeter, United Kingdom
Attendance: Limited
Contact: http://www.iges.org/c20c/

North Atlantic Subpolar Gyre Workshop
19-20 March 2007
Kiel, Germany
Attendance: Open
Contact: http://www.ifm-geomar.de/index.php?id=subpolar-gyre

Climate Prediction Applications Science Workshop
20-23 March 2007
Seattle, Washington
Attendance: Open
Contact:
http://www.cses.washington.edu/cig/outreach/workshopfiles/cpasw07/

Int'l Oceanographic Data and Informatino Exchange (IODE)
16-20 April 2007
Trieste, Italy
Attendance: Open
Contact: http://www.iode.org

CLIVAR Indian Ocean Panel Meeting
23-25 April 2007
South Africa
Attendance: Invited
Contact: http://www.clivar.org

Seventh Workshop on Decadal Climate Variability
30 April-3 May 2007
Kona, Hawaii
Attendance: Open
Contact: http://www.decvar.org/workshops_conferences.php

WCRP Workshop on Seasonal Prediction
4-6 June 2007
Barcelona, Spain
Attendance: Open
Contact:
http://www.wmo.ch/web/wcrp/AP_SeasonalPrediction.html

IEEE Oceans '07
18-21 June 2007
Aberdeen, Scotland
Attendance: Open
Contact: http://www.oceans07ieeeaberdeen.org/

U.S. CLIVAR Summit
23-25 July 2007
Annapolis, Maryland
Attendance: Invited
Contact: www.usclivar.org

assuming that there is both uncertainty in the initial condition and uncertainty as the forecast evolves. The blue rms error curve in both Figure 2A and 2B corresponds to the case of no initial conditions uncertainty and much reduced uncertainty as the forecast evolves. The blue curves in both panels are identical. Finally, the yellow curve in Fig. 2b corresponds to the rms error assuming no initial condition uncertainty, but with uncertainty as the forecast evolves. By comparing both sets of yellow curves with the blue we conclude the following:

(i) Initial condition uncertainty leads to a very rapid initial loss of predictability (Figure 2A yellow compared to Figire 2B yellow).

(ii) Uncertainty as the forecast evolves clearly limits predictability (Figure 2B yellow vs. blue), but initial condition uncertainty is the dominating factor.

(iii) The predictability curves lie considerable below the errors in actual forecasts (not shown). This indicates that the model estimate of the limit of predictability is much longer than is currently realized in actual forecast mode.

As noted earlier, despite the fact that this one of the best ENSO forecast models, the argument that initial condition uncertainty dominates is a model dependent result, and is highly influenced by model error. In fact, current thinking suggest the "ENSO mode" of the coupled model is significantly different from the "ENSO mode" of nature; therefore, the rapid rms error growth at the initial time may be influenced disconnect between the model and observed "ENSO mode." Nevertheless, these results do suggest that reducing initial condition uncertain, particularly in the ocean, will improve prediction, and that correctly initializing the "ENSO mode" of the coupled model will also have a significant impact on forecast skill. In addition, correctly representing the statistics of weather noise in climate forecast models is likely to improve ENSO prediction skill. All of these results indicate significant potential to improve ENSO forecast, however, the importance of model error in this regards cannot be overstated. ■

(*Decadal Workshop continued-from page 7*)

the tropical Atlantic and the possibility of atmospheric predictability on seasonal and longer timescales; and dynamics and predictability of the ocean and its meridional overturning circulation.

Discussions of a research program for moving forward

It was argued that three significant investments made by the climate community over the past decades make a focus on Atlantic decadal predictability timely. Firstly, TOGA and post-TOGA research has: refined our understanding of the role of coupled interactions on the tropical Pacific in global climate; led to the development of improved coupled climate models; led to the implementation of operational seasonal forecast systems, a climate ocean observing system in the Pacific, and ocean data assimilation systems for the initialization of the forecasts. Secondly, the IPCC process has led to the development of a generation of models which are starting to give information about the regional impacts of global warming and are capable of simulating global climate variability and associated regional impacts of this on seasonal to decadal timescales. Thirdly, the basics of a global climate ocean observing and synthesis system are being put in place as a legacy of WOCE. This global observing/analysis system provides the foundation for developing a nowcasting capability for decadal variability, providing the initial conditions for predictability studies, improvements in the required models, and refinements in the observing capability required for this task.

It was recognized that ultimately a decadal prediction system needs to account for global interactions associated with climate variability and change (indeed the models and data assimilation systems which would be used would be global from the start). However, recent events such as the onset of a decade of active Atlantic hurricane activity since 1995, which has been linked both to the AMO and to anthropogenic forcing, indicates a need for a special focus on the Atlantic. Moreover, the latest generation of climate models is leading to new insights into both the regional and global impacts of decadal Atlantic temperature changes.

The primary components of such a decadal prediction program would be: A) a diagnostics program including data-model comparisons; B) predictability studies; C) a program of experimental decadal predictions; D) tools for decadal predictions – ocean/coupled models, ocean/ice state estimations tested against data, and evaluation/design of ocean observations system; and E) prototype outlooks.

Outcomes of such a program would include: i) an improved understanding of the roles and mechanisms of natural and anthropogenically produced decadal variability in the Atlantic and its global impacts; ii) an evaluation of the potential predictability of aspects of this decadal variability; iii) a prototype system for decadal predictions – this would include an ocean nowcasting capability and design of the required observing system; iv) ensemble decadal outlooks for the next decades. These outlooks would be for the MOC, SST, heat content, and perhaps for sea ice, sea level, and temperature and precipitation over adjacent continents. A special focus would be on the decadal outlook for Atlantic hurricane activity. Ocean state projections could also be used to drive models of ocean ecosystems with applications to marine conservation and fisheries.

Next Steps

A meeting on the Atlantic observing/synthesis system for the Atlantic ocean circulation and its meridional overturning circulation at AOML, Miami in January, 2007, and a Climate Decadal Variability workshop with potential international partners in Kona, Hawaii in April/May 2007. ■

U.S. CLIVAR

2006 Summit Meeting Highlights:

Increasing Importance of Extremes and Decadal Variability/Predictability

The 2006 U.S. CLIVAR Summit, held in Breckinridge, CO, focused on identifying a few scientific challenges that warrant increased levels of coordination and community planning/organization. In addition, during breakout meetings, the three U.S. CLIVAR Panels addressed Panel-specific issues. For example, the Process Studies and Model Improvement (PSMI) Panel developed initial ideas on "best practices" for intensive field campaigns in order to enhance their legacy and develop constructive linkages to model evaluation and development activities. They also discussed ongoing needs and opportunities for systematically evaluating and improving (through process-oriented research) climate models. The Predictability Prediction, and Applications Interface (PPAI) Panel continued developing plans and activities (including a session at the Fall AGU meeting) to best characterize climate predictability on a range of time scales (from seasonal through decadal). Their efforts were highlighted during the recent Climate Diagnostics and Prediction Workshop. The Phenomena, Observations, and Syntheses (POS) Panel addressed observational needs for decadal variability/prediction systems as well as heard several updates on ocean observation system development and data management issues. In Plenary, the first two US CLIVAR Working Groups, Ocean Salinity and MJO, reported on their activities.

One of the objectives of the Summit was to identify a few strongly compelling scientific areas of research that would attract the interest of agencies and the scientific community, for which improved coordination (through U.S. CLIVAR) would accelerate the rate of discovery, knowledge, and communication of research findings to other communities and U.S. CLIVAR "customers". These research areas should be strongly be motivated by societally relevant questions; be responsive to one or more agency's immediate mission needs or interests; attract the participation by the broader research community and U.S. CLIVAR Panels and Working Groups; and leverage existing U.S. and international research investments.

After extensive discussion, two such research areas were identified: a) decadal variability and its prediction; and b) extreme events - drought. A Drought Working Group within U.S. CLIVAR is now being formed to coordinate and analyze model experiments aimed at identifying important mechanisms related to multi-year droughts. Additionally, an informal group organized by John Marshall (and others – see related article), is focusing on developing experimental decadal forecasts. These initial activities, although small, bring early focus to these important research areas. As the new year approaches, U.S. CLIVAR will better crystallize the motivation, outlook, and research strategies targeting these research areas.

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