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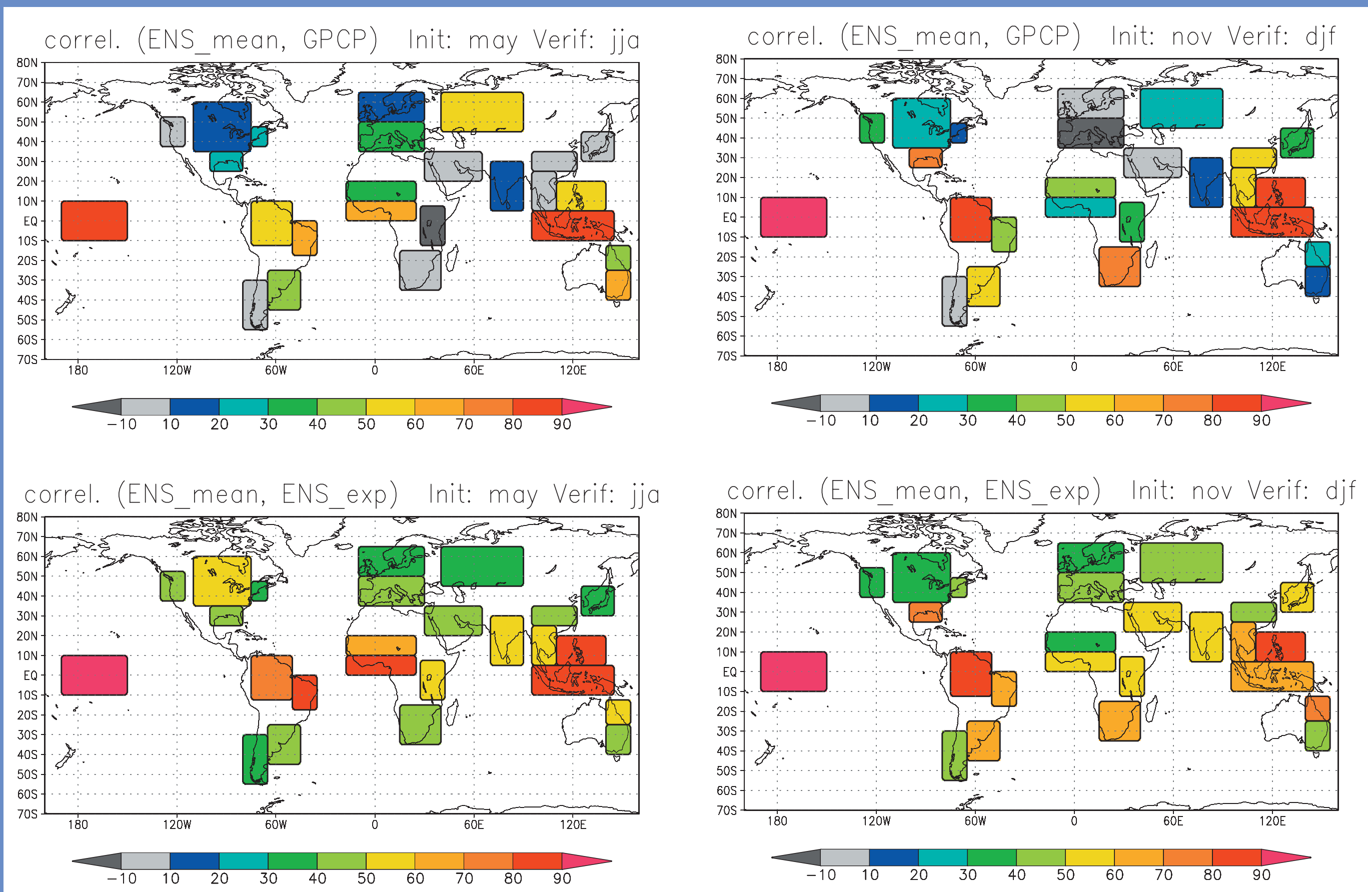
Seasonal Prediction

From Molteni et al, page 7: ECMWF Seasonal Forecast System 3



The anomaly correlation for area-averaged seasonal rainfall anomalies (JJA left, DJF right) in selected regions of the world for ECMWF System 3 seasonal forecasts. The upper panels show the correlation between forecasts and observations - in some regions this is quite high, in others it is near zero. The lower panels show the model estimate of the predictability limit, in other words the correlation that would be obtained with a perfect model. In some places the level of potential predictability is much higher than the skill presently achieved.

CLIVAR is an international research programme dealing with climate variability and predictability on time-scales from months to centuries. **CLIVAR** is a component of the World Climate Research Programme (WCRP). WCRP is sponsored by the World Meteorological Organization, the International Council for Science and the Intergovernmental Oceanographic Commission of UNESCO.

WCRP
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Thanks to Ben Kirtman and Anna Pirani for all their work in editing this edition of Exchanges. Together with its key focus on Seasonal Prediction, this edition also announces the publication of Volume 2 of the WOCE Atlas Series, outlines developments in planning of the Southern Ocean Observing System (SOOS) and summarises the outcomes of the 4th session of the CLIVAR Indian Ocean Panel (see pages 36-39). The next edition (January 2008), focussing on the theme of "Furthering the Science of Ocean Climate Modelling" will include an account of the CLIVAR SSG meeting, which took place in Geneva from 11-14 September 2007.

Howard Cattle

Editorial

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This special issue of Exchanges on seasonal prediction builds on the success of the 1st WCRP Workshop on Seasonal Prediction that brought together around 180 participants from 30 countries of the seasonal prediction, climate dynamics and seasonal forecast applications community in Barcelona, Spain on 4-7 June 2007. The Workshop was a landmark in the ongoing seasonal prediction assessment being led by CLIVAR and the World Climate Research Programme (WCRP), and nearly all of the contributions to this issue are based on presentations made at the Workshop. In particular, the opening article gives a summary of the WCRP Position Paper on assessing the quality and value in seasonal prediction that is being prepared by the Workshop coordinators through an extensive consultation process with all the Workshop participants.

The articles presented here span the comprehensive range of topics that are being currently addressed by the seasonal forecast operational, research and applications community and contribute to the assessment of the regional skill and socio-economic importance of forecasts. It is clear that increasing precipitation forecast skill is one of the major challenges facing the community, as illustrated by the front page image (Molteni et al., 2007, Exchanges, this issue) that shows the potential predictability of precipitation in different regions of the World. State-of-the-art dynamical and empirical forecast systems, the potential for improvement in skill from multi-model, combined dynamical-empirical and calibration techniques, are evaluated. The issue includes articles looking at the prediction of the onset of the monsoon and the impact of phenomena such as ENSO teleconnections and Indian Ocean SST anomalies on seasonal forecasts from South Africa to Australia and East Asia. Innovative applications of forecasts are presented with an example demonstrating downscaling precipitation to derive river flow forecasts and another with the use of multi-model forecasts coupled to a process-based malaria model to assess the applicability of seasonal forecasts for Africa-wide epidemic malaria forecasts.

This issue of exchanges provides a synopsis of the Workshop and introduces the key elements of the WCRP seasonal prediction position paper, which is available at http://www.clivar.org/organization/wgsip/spw/spw_position.php. This position paper is a living document in the sense that it will be refined and evolve over time as we develop better metrics for measuring seasonal prediction capabilities and better prediction methodologies. In addition, as we learn how to make better use of seasonal prediction information this too will be documented in the position paper.

One of the overarching goals of the WCRP is to determine the predictability of the complete physical climate system on time scales of week to decades. CLIVAR, through its leadership of the WCRP Task Force on Seasonal Prediction (TFSP) and the Working Group on Seasonal to Interannual Prediction (WGSIP) has been coordinating the assessment of current seasonal-to-interannual predictive capabilities, and defining the new frontier in climate prediction research by designing the experimental framework for sub-seasonal to decadal complete physical climate system prediction. By the complete physical climate system, we mean contributions from the atmosphere, oceans, land surface, cryosphere and atmospheric composition in producing regional and sub-seasonal to decadal climate anomalies. This experimental framework is described at the WGSIP web site (http://www.clivar.org/organization/wgsip/wgsip.php). The TFSP and WGSIP believe that this experimental framework is a path to improve prediction quality and use for societal benefit.

The First WCRP Seasonal Prediction Workshop

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This article describes the motivation and outcomes of the First WCRP Seasonal Prediction Workshop, which was held June 4-7 in Barcelona Spain, bringing together climate researchers, forecast providers and application experts. The main purposes were to describe the current status and main limitations regarding seasonal forecast skills and applications, and to make recommendations to improve both of these aspects. It is clear that there is substantial scope for improving skill by reducing model biases and including a wider range of climate processes, and improving benefits through better communication of more appropriate information.

Introduction

Our ability to predict the seasonal variations of the Earth's tropical climate dramatically improved from the early 1980s to the late 1990s. This period was bracketed by two of the largest El Niño events on record: the 1982-83 event, whose existence was unrecognized until many months after its onset; and the 1997-98 event, which was well monitored from the earliest stages, and predicted to a moderate degree by a number of models several months in advance. This improvement was due to the convergence of many factors including a concerted international effort to observe, understand and predict tropical climate variability, the application of theoretical understanding of coupled ocean-atmosphere dynamics, and the development and application of models that simulate the observed variability.

After the late 1990s, our ability to predict tropical climate fluctuations reached a plateau with little subsequent improvement in quality. Was this a result of a fundamental change in the predictability of the climate system due to either natural or anthropogenic forcing, or the emergence of a critical failing in the models used to make predictions or merely a sampling effect? Have we accounted for all the critical interactions among all the elements of the climate system (ocean-atmosphere-biosphere-cryosphere)? Are the observations adequately blended with the models to make the best possible forecasts?

About a third of the world's population live in countries influenced significantly by climate anomalies. Many of these countries are developing countries whose economies are largely dependent upon their agricultural and fishery sectors. The climate forecast successes of the 1980s and 1990s brought great promise for societal benefit in the use and application of seasonal forecast information. However this promise of societal benefit has not been fully realized, in part, because there have not been adequate interactions between the physical scientists involved in seasonal prediction research and production, applications scientists, decision makers and operational seasonal prediction providers. The issues and problems go beyond merely improving forecast quality and making forecasts readily available. The physical scientists need to actively facilitate and understand how the forecasts can be used in order to make useful improvements to forecast products.

One of the overarching objectives of the World Climate Research Programme (WCRP) is to facilitate analysis and prediction of Earth system variability and change for use in an increasing range of practical applications of direct relevance, benefit and value to society. In order to, in part, meet this objective the WCRP commissioned the Task Force on Seasonal Prediction (TFSP) to assess current seasonal prediction capability and skill considering a wide range of practical applications, and to enable the development and implementation of numerical experimentation specifically designed to enhance seasonal prediction skill and the use of seasonal forecast products for societal benefit.

As part of the seasonal prediction capability assessment, the TFSP in collaboration with the core programs of the WCRP (CLIVAR, CliC, SPARC and GEWEX) and the World Climate Programme (WCP) organized the First WCRP Seasonal Prediction Workshop, which was held June 4-7 2007 in Barcelona Spain. This article summarises the key outcomes and recommendations of this workshop. This WCRP Position Paper on Seasonal Forecasting that is being prepared by the Workshop participants is intended to go beyond merely summarizing the workshop presentations; indeed we specifically avoid this sort of summary. The main purpose is to provide definitive statements regarding current skill in seasonal prediction with emphasis on surface temperature and rainfall and how the forecasts are currently being used for societal benefit. In addition, the report outlines a set of specific recommendations for improving seasonal prediction skill and enhancing use of seasonal prediction information for applications.

The Workshop focused on addressing two basic overarching questions:

(i) What factors are limiting our ability to improve seasonal predictions for societal benefit?
(ii) What factors are limiting our ability to use seasonal predictions for societal benefit?

In addition to addressing these questions, the workshop participants developed recommendations spanning both the physical and application sciences for how to overcome these limiting factors. The workshop brought together the diverse seasonal prediction community. This includes researchers of the physical climate system and forecast methodology, operational forecast providers and forecast applications experts. There were approximately 180 attendees that represented diverse international interests both in the physical and application fields. Approximately 30 countries or so from the WMO Regions I-IV (Africa, Asia, South America, North and Central America, Southwest Pacific and Europe) were represented. Representatives from all the major operational seasonal prediction centers and funding agencies were in attendance.

This summary of the workshop is organized as follows:

(1) We present some critical common language regarding the assessment of seasonal prediction. Developing a common language for assessing seasonal prediction is critical to successful interaction among forecast providers, forecast users and forecast researchers, and the importance of this agreed upon language cannot be over stated.
(2) We enumerate the overarching consensus among the workshop participants regarding the current status and future prospects of seasonal prediction. These consensus statements required considerable discussion among the workshop participants and invited experts, and carry the full weight of the seasonal prediction community.
(3) The workshop identified a simple set of metrics for assessing seasonal prediction quality, which provide a key benchmark of evaluating future improvements. These metrics are presented here; however, the workshop participants recognized the importance of allowing these metrics to be refined over time. In fact, the workshop report is a "living" document that will be refined and updated in the future and made available online to the entire community.

A Common Language for Assessing Seasonal Prediction

The need for an authoritative statement on the skill of seasonal, and other extended-range, predictions has long been recognised. Several audiences for such a statement exist, including development scientists, forecast producers and distributors, managers, funders, and the wide range of individuals outside the climatological community who either process the forecast information to advise others or who take decisions based on that information and who will be referred to collectively below as 'users'. Each audience has its own specific requirements for such a statement, and the information processing necessary to produce the statement varies accordingly. In order to simplify this current statement the target audience is assumed to be development scientists and users, although others will gain benefit.

The term 'skill' covers a complex array of issues; just two will be covered here, *quality* and *value*.

(i) *Quality* refers to the technical measurement of forecast performance; *quality* is of prime concern to scientists and is often queried by users.
(ii) *Value* relates to the practical benefits achieved through decision making based on forecast information, usually amongst other information, and while of fundamental concern to the user should also stimulate scientists.

Overarching Consensus Statements

(1) The workshop participants unanimously agreed that the maximum predictability of the climate system has yet to be achieved in operational seasonal forecasting.

This position is based on the recognition that: (i) model error continues to limit forecast quality and that (ii) the interactions among the elements of the climate system are not fully taken into account and may lead to improved forecast skill. The fact that model error continues to be problematic is evident from the need for and success of calibration efforts and the use of empirical techniques to improve dynamical model forecasts. Land-atmosphere interactions are, perhaps, the most obvious example of the need to improve the representation of climate system interactions and their potential to improve forecast quality.

(2) Multi-model methodologies are a useful and practical approach for quantifying forecast uncertainty due to model formulation.

There are open questions related to the multi-model approach. For example, the approach is ad-hoc in the sense that choice of models has not been optimized. Nor has the community converged on a best strategy for combining the models. Multi-model calibration activities continue to yield positive results, but much work needs to be done. These issues as well as others require additional research. It is also important to note that the multi-model approach should not be used to obviate the need to improve models.

(3) A common agreed upon baseline procedure for assessing seasonal prediction skill is critical for documenting future improvement.

This includes best practices in forecasting and appropriate validation/verification techniques; and recognition of the non-stationarity of the climate system. These best practices need to be developed for both global and regional prediction systems. The Position Paper and its future evolution in collaboration with WCRP and WCP is an effective process for developing and refining these best practices. The workshop participants argued that there is an immediate need for the international seasonal prediction community to come to a consensus on best practices. Some of these issues are touched upon in the Position Paper, but more work is needed. Recognizing the non-stationarity of climate variability is important in terms of assessing quality and enhancing value of season forecasts. As such seasonal forecasts, particularly retrospective forecasts, should be made with observed climate forcing as noted in the TFSP experimental design. Commonality of physical processes and of models is an explicit link across predictive time scales (e.g., seasonal to climate change). This makes seasonal forecasting a vital test bed to assess the reliability of longer-range predictions. This is particularly true when applications, such as those in agriculture and health are considered.

(4) Model errors, particularly in the tropics, continue to hamper seasonal prediction skill.

The importance of reducing model error cannot be over stated. There are a number of strategies for improving models including a better representation of the interactions among the elements of the climate system, inclusion of biogeochemical cycles, and substantial increases in spatial resolution. All of these strategies need to be vigorously pursued; however, international and nation coordination and commitment is seriously lacking.

(5) Forecast initialization is an area that requires active research. Ocean data assimilation has improved forecast quality; however, coupled data assimilation is an area of active research that is in need of enhanced support and perhaps international coordination.

There is significant evidence that coupled ocean-atmosphere data assimilation is likely to improve forecast quality. Compatible land surface initialization strategies are actively being pursued in GEWEX and continued coordination with the seasonal prediction community is warranted.

(6) Observational requirements for seasonal prediction and the development of applications of seasonal predictions are not being adequately met.

While defining the observational requirements for seasonal prediction was beyond the scope of this workshop, the participants agreed that this is an issue that requires attention.

(7) Verification should also be undertaken routinely using simplified but multivariate driven dynamical applications models.

The relationship between forecast quality in applications models and meteorological models is often highly non-linear. Quality in the prediction of seasonal mean rainfall may not translate into quality in the prediction of crop yield, for example. Thus application models can provide additional metrics of forecast quality. Furthermore, these metrics usually have a specific user group in mind.

(8) Web based tools need to be developed to allow users of the prediction information to tailor the underlying climate information more easily to their needs (e.g. climate range/thresholds, spatial scale(s)).

Progress on this front is critical to improving the value of seasonal forecasts.

(9) Although there are many examples of seasonal forecast application (e.g., health, agriculture, water management), there is potential to do much more.

More progress needs to be made in bringing seasonal prediction providers and seasonal prediction users together. More work is required to develop the production and understanding of probabilistic forecasts. Understanding of what is predictable and what is not predictable need to be enhanced. The importance of predicting 'extremes' (even top and bottom quintile categories are extreme for seasonal prediction, and probability forecasts are increasingly presented in these terms) was also noted.

(10) The research community has not adequately quantified what is and what is not predictable.

Indeed, the Position Paper, as it evolves over time should include, where possible, unambiguous statements regarding what is predictable and what is not predictable.

Assessing Seasonal Prediction Quality

The workshop participants made presentations on validating and assessing the state-of-the-art and quality in seasonal forecasts by bringing together retrospective forecast data issued from international research projects (i.e., SMIP2/HFP DEMETER, ENSEMBLES, and APCC) as well as data available from operational centers. Assessments were made in terms of scientific quality and factors limiting improvement. The presentations highlighted issues important for interfacing seasonal forecasts with applications including calibration, downscaling and validation, and determining whether there is an emerging consensus on approach and methodology. The workshop participants addressed seasonal prediction from a wide-ranging multi-disciplinary perspective looking at the role of cryospheric processes, stratospheric processes and air-land interactions on seasonal prediction, as well as the role of ocean initialization, aiming to explore additional source of potential seasonal predictability. A number of the presentations emphasized the quality of seasonal prediction in the monsoon regions of Africa, Asia and South America.

Based on these presentations the workshop participants converged on two metrics for an overarching assessment of the quality of seasonal prediction. These are the multi-model Brier Skill Score, described in more detail below, and the quality of the predicted SST in the Eastern Pacific (i.e. the Nino3.4 region). It was clearly acknowledged that these metrics were not sufficient for use in applications or to improve the quality of the forecasts. Much more detailed information is required, but well beyond the scope of the Position Paper. These metrics, however, do provide a simple benchmark from which progress can be measured. It was also acknowledged that future refinements and enhancement may be required and the workshop participants urged that this assessment be viewed as an evolving or "living" document that will be periodically updated and reviewed.

Multi-model Bier Skill Score (BSS)

This metric is a multi model Brier Skill Score for seasonal mean (DJF and JJA) 2m temperature and rainfall over 21 standard land regions (Giorgi and Francisco, 2000). This particular forecast quality metric is discussed in detail in a companion paper in this volume (see Palmer et al, 2007) and in the peer review literature (see Palmer et al. 2008). These regions, seasons and lead times are not necessarily the optimum for all users and forecast providers. Nevertheless, they do provide a reasonable overall measure of state-of-the-art quality. The one month lead seasonal mean multi-model BSS based on DEMETER data (Palmer et all., 2004) is summarized in Table 1. Here the BSS is calculated for binary events (i.e., precipitation exceeds the upper tercile, $E^+_P(x)$; precipitation exceeds the lower tercile, $E^-_P(x)$ and similarly for temperature: $E^+_T(x)$, $E^-_T(x)$). Positive values indicate reliable forecasts and underlined values indicate greater than 90% confidence in the reliability. Negative underlined values indicate that the multi-model ensemble reliably fails to predict the occurrence of the event. Whether the negative underlined values provide useful information is the subject of debate and research.

Overall it is clear that 2m temperature is more reliably predicted than precipitation regardless of season. Tropical regions generally show more temperature reliability (i.e., Central America, Amazon Basin, Western Africa), although there are sub-tropical regions of considerable forecast quality (i.e., Tibet). While some regions can be reliably predicted in both JJA and DJF, there is significant seasonality in 2m temperature forecast quality.

In contrast to 2m temperature, the models have significant difficulty capturing the rainfall variability over these land regions. There is notable forecast reliability in the local summer seasons over the Amazon Basin and Southeast Asia. Elsewhere the precipitation forecast reliability is desultory.

In defining this metric, the workshop participants identified two points that highlight the importance of improving models: (i) calibration can improve the reliability and (ii) exploiting known dynamical and physical relationships (i.e., teleconnections) can also be used to improve the reliability. The fact that forecast quality can be improved using these techniques indicates that models and predictions can and should be improved.

Conclusion

The workshop, the follow-on WCRP Position Paper on Seasonal Prediction, and the TFSP prediction experiments (http://www.clivar.org/organization/wgsip/tfsp.php) represent the necessary steps in a comprehensive (quality and value) seasonal prediction assessment. The consensus statements that are part of the WCRP seasonal prediction Position Paper carry the full weight of the entire seasonal prediction community. The consensus statements were discussed and vetted in great detail at the workshop and have been made available for comment from scientists and researchers who were unable to attend the workshop. Indeed, the feedback from both the workshop participants and those unable to attend has lead to significant refinements.

As noted above, the workshop participants felt very strongly that the WCRP seasonal prediction Position Paper be a living document, not only to embellish upon the assessment metrics, but also to clearly document future seasonal prediction improvements. In particular, the TFSP experiments require a much more "comprehensive" view of seasonal prediction. By comprehensive, we mean that the TFSP is hypothesizing that there will be substantive improvements in seasonal prediction if and only if we include all the interactions among the components of the climate system. This WCRP seasonal prediction paper necessarily needs to document the results of the TFSP experiments that should become available in late 2009.

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Region	2m Temperature				Precipitation			
	JJA		DJF		JJA		DJF	
	$E_T^-(x)$	$E_T^+(x)$	$E_T^-(x)$	$E_T^+(x)$	$E_P^-(x)$	$E_P^+(x)$	$E_P^-(x)$	$E_P^+(x)$
Australia	**10.7**	**10.1**	1.3	-0.4	-1.3	-2.5	-3.1	-3.6
Amazon Basin	**14.4**	9.1	**23.4**	**25.7**	2.2	2.1	**9.5**	**8.9**
Southern South America	**8.5**	**8.2**	-1.2	1.8	**7.8**	5.0	-0.7	-2.8
Central America	**12.1**	**9.9**	**14.8**	6.3	2.6	-0.7	8.7	8.5
Western North America	**6.5**	**7.7**	3.9	2.3	3.2	**5.5**	-0.6	0.0
Central North America	-4.1	-3.6	**-7.5**	0.3	-1.8	**-7.0**	3.7	5.3
Eastern North America	0.6	5.7	4.1	9.5	**-4.5**	**-8.3**	**9.2**	6.0
Alaska	3.0	2.1	0.0	-0.7	-0.1	0.3	2.4	4.9
Greenland	3.6	4.2	**8.0**	5.8	**-1.4**	-0.5	-2.1	-2.0
Mediterranean Basin	**7.6**	**10.7**	3.2	3.2	-0.5	0.1	1.6	-0.9
Northern Europe	-4.4	-4.2	4.8	2.9	-1.0	1.9	-1.1	-0.9
Western Africa	**10.4**	**11.8**	**18.1**	**17.2**	-1.6	-2.0	**-4.9**	**-3.5**
Eastern Africa	**12.6**	5.8	**13.3**	**10.3**	0.1	-0.3	1.2	0.6
Southern Africa	5.6	-1.1	**15.9**	**15.7**	0.7	-1.2	5.4	3.6
Sahara	**7.6**	**7.4**	6.9	3.9	**-2.6**	**-4.8**	**-2.7**	**-2.7**
Southeast Asia	10.7	5.9	8.7	**18.1**	**14.7**	**10.3**	3.4	2.5
East Asia	**4.7**	**7.9**	**10.8**	**10.0**	0.6	-1.0	-1.6	-0.9
South Asia	4.9	**13.1**	**7.6**	**8.6**	-1.6	**-3.0**	2.0	0.5
Central Asia	0.8	3.8	1.3	-0.4	0.5	0.1	-3.1	-3.6
Tibet	**10.7**	**10.1**	**23.4**	**25.7**	-1.1	0.0	**9.5**	**8.9**
North Asia	**14.4**	9.1	-1.2	1.8	-1.3	-2.5	-0.7	-2.8

Table 1: Forecast quality of the DEMETER multi-model seasonal re-forecasts in terms of Brier Skill Scores (BSS) for near-surface temperature and precipitation upper and lower tercile categories in JJA and DJF for 21 standard land regions (multiplied by 100). The scores for E±T,P(x) have been computed over the re-forecast period 1980-2001 using seasonal means from 1-month lead ensembles started on the 1st of May/November. Bold underlined numbers indicate scores with a probability p≥0.9 that a random sample based on a 10,000 bootstrap re-sampling procedure would yield BSS<0 (significantly negative) or BSS>0 (significantly positive).

Seasonal Forecast Datasets – A Resource for Calibrating Regional Climate Change Projections?

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Seasonal forecasts are of value for many different applications. Here we propose a potential new application - as a resource for calibrating probabilistic regional climate change projections in the light of model error. This paper is based on a more extensive paper submitted for publication in the peer-reviewed literature (Palmer et al., 2008).

Anthropogenic climate change (ACC) is currently top of the political agenda, and public awareness of the threat of climate change is very high. Since significant climate change now seems inevitable, government and society alike are asking about the sort of infrastructure investments required to adapt to climate change. Informed decisions on such investments will require reliable projections of not only regional temperature, but also of regional precipitation, e.g. towards wetter or drier winters.

ACC is a major theme of CLIVAR as well as being a cross-cutting activity within WCRP. CLIVAR's perspective on ACC arises from the project's focus on natural modes of variability: how does ACC influence the evolution of these natural modes? This type of question is critical since regional precipitation is strongly linked to circulation patterns; hence changes in precipitation can arise from changes either in the frequency of occurrence, or in the structure, of the natural modes of climate variability. For example, the drought that affected Southern England between 2004 and 2006 was directly associated with persistent blocking anticyclone activity, whilst the exceptionally wet summer of 2007 was associated with a persistent trough over Northern Europe. Are these types of winter blocking anticyclone or summertime persistent trough likely to become more prevalent under ACC?

The IPCC Fourth Assessment Report (AR4) multi-model ensemble provides quantitative probabilistic estimates of these types of questions. As far as the UK is concerned, the AR4 ensemble does not indicate any increase in probability of blocking activity in winter, or persistent drought in summer. Indeed there is almost a consensus amongst the AR4 integrations that winters over the UK will get wetter, and near consensus that summers will get drier.

At first sight, it might appear unlikely that seasonal forecast datasets could have much bearing whether or not these probabilistic ACC projections are reliable, since ACC is the consequence of radiative forcing perturbations, whilst seasonal forecasts exploit the potential predictability of, for example, coupled ocean-atmosphere modes. However, because of the nonlinearity of the climatic equations of motion, radiative forcing perturbations would rapidly excite the natural modes of climate variability. Indeed the notion that diagnosis of seasonal forecast datasets could have a bearing on the reliability of projections of ACC, is entirely consistent with the CLIVAR perspective on ACC.

A well-studied multi-model ensemble seasonal forecast dataset was created as part of the DEMETER project (Palmer et al., 2004). The seven component models of the DEMETER project are each IPCC-class global coupled ocean-atmosphere models. Probabilistic Brier skill scores for seasonal-mean precipitation have been estimated for all the Giorgi (Giorgi and Francisco, 2000) regions. A summary of these results is given in an accompanying article in this issue (Kirtman et al., 2007). Results are quite mixed: some regions show positive levels of skill, others are clearly negative. The first row of Figure 1 (page 19) shows reliability (also known as attribute) diagrams (Wilks, 1995) for two of the Giorgi regions: one where the reliability is high (Western North America), the other where reliability is low (Southern Europe-Mediterranean).

What is the cause of seasonal-forecast unreliability? When a reliability line is flatter than the ideal 45° slope, this indicates that the ensemble is over-confident, i.e. forecast probabilities are higher (lower) than expected when the event occurs a high (low) number of times. This suggests that the ensemble is not properly capturing the sources of forecast uncertainty. These forecast uncertainties arise from errors in either the initial conditions, or the model formulation, or both. There is no obvious reason to suppose that uncertainty in initial conditions is being inadequately sampled in the DEMETER dataset. However, there is reason to suppose that errors in model formulation are not being fully sampled by the DEMETER models. For example, it has been established that each of the DEMETER models inadequately simulates persistent blocking anticyclones; indeed present-day climate models have difficulty simulating many types of persistent climate anomaly. As such, the types of seasonal-precipitation anomaly discussed above are associated with precisely the persistent regional circulation regimes that models have difficulty in simulating.

Putting these results together, it can now be seen how information concerning the reliability of seasonal precipitation anomalies is relevant to assessing the reliability of climate change projections of seasonal-mean precipitation. Of course, this does not imply that by assessing climate change models in seasonal forecast mode we have a necessary and sufficient test of the reliability of the climate change projections: for climate change there are clearly relevant processes which occur on longer timescales than can be assessed in seasonal forecast mode. Rather we view the assessment with seasonal forecasts as only providing a necessary test on the reliability of the climate-change projections.

In order to use the seasonal forecast data quantitatively, we propose the following methodology. First, for selected regions, the relevant reliability diagram is used to define a probability forecast calibration such as is used in probabilistic weather prediction (Toth et al., 2006). Such a calibration will discount probabilities (back towards climatological values) in regions of strong probability forecast unreliability. Secondly, a calibration is applied to the AR4 probabilities in the same region.

This two-part method is illustrated in Figure 1 where we study lower tercile precipitation for June-August in two land areas. The top-row panels show the DEMETER seasonal forecast reliability diagrams. A best fit regression line has been drawn through the points in the reliability diagram. The middle-row panels show the raw, i.e. uncalibrated ratio of probabilities of lower tercile precipitation based on the IPCC AR4 data for the last two decades of the 21st century and the end of the 20th Century. The probabilities are based on the multi-model ensemble. The panels in the bottom row show the AR4 probabilities, calibrated using the DEMETER regression line of the reliability diagrams.

Details of the calculation are given in Palmer et al. (2008); here we focus on the main results. For the Western North American region, where the DEMETER seasonal forecasts were found to be reliable, the calibration procedure hardly alters the raw AR4 probabilities. Hence the basic AR4 prediction that there is a substantial increase in the probability of lower tercile rainfall due to climate change remains unaffected by seasonal forecast calibration for Western North America. However, the corresponding prediction for the Mediterranean region is substantially discounted by the calibration, and the change in probability compared with the 20th century value of one third is now much smaller.

In principle such calibrations could be of importance for relevant climate adaptation decisions. Broadly speaking, if infrastructure at cost C can be implemented to protect society against a particular climate change, and if the economic and social losses arising from unprotected climate change equal L, then the decision to invest in such infrastructure depends on whether the relevant climate change probability exceeds C/L.

These results illustrate the potential value of developing seamless forecast systems, i.e. systems that span weather and climate timescales. In such systems the validation of forecasts on timescales where validation data exists can be used to assess the reliability of the forecasts on timescales where validation data does not exist. The concept of a seamless prediction system is a focus in the recent strategic framework of the World Climate Research Programme, and is entirely consistent with the objectives of the CLIVAR project.

Acknowledgements
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ECMWF Seasonal Forecast System 3

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1. Introduction

ECMWF has been running a seasonal forecast system since 1997, and in March 2007 a new forecast system, known as System 3 (S3, Anderson et al, 2006) was introduced. The system consists of the atmospheric and oceanic components of the coupled model as well as the data assimilation scheme to create initial conditions for the ocean, the coupling interface linking the two components and the strategy for ensemble generation. For all ECMWF systems so far, there is no dynamic sea-ice model; the initial conditions are based on the observed sea-ice limit but thereafter the sea-ice evolves according to damped persistence.

New forecast systems are introduced only occasionally, both because of the work involved and the value of stability for users: System 1 (S1) became effectively operational in late 1997, System 2 (S2) started running in August 2001, and System 3 started running in August 2006 and became the operational version in March 2007. The atmospheric model for S3 is cycle 31r1 (Cy31r1) of the IFS. The horizontal resolution has been increased from TL95 to TL159 (with the corresponding grid mesh reduced from 1.875° to 1.125°), and the vertical resolution is increased from 40 levels to 62 levels, extending up to ~5 hPa. Major changes have taken place in the ocean analysis system for S3, though the HOPE ocean model is little changed from the version used in S2.

As in S2, the ocean initial conditions in S3 are provided not from a single ocean analysis but from a 5-member ensemble of ocean analyses, created by adding perturbations to the wind forcing used in the analysis. The atmospheric initial conditions, including land conditions, come from ERA-40 for the period 1981 to 2002 and from ECMWF operational analyses from 2003 onwards.

The real-time ensemble set consists of 41 members in S3, and the calibration set consists of 11 members spanning the 25-year period 1981–2005, so creating a calibration probability distribution function of 275 members. Each of these ensembles has a start date of the first of the month. The initial atmospheric conditions are perturbed with singular vectors and the ocean initial conditions are perturbed by adding sea surface temperature perturbations to the 5 member ensemble of ocean analyses. Stochastic physics (stochastic perturbation of physical tendencies with a six-hour decorrelation timescale) is active throughout the forecast period.

S3 seasonal integrations are 7 months long (S2 integrations were only 6 months). Additionally, once per quarter an 11 member ensemble runs to 13 months, specifically designed to give an "ENSO outlook". Back integrations have also been made to this range, once per quarter, with a 5 member ensemble.

2. The ocean analysis

The ocean analysis for System 3 extends back to 1959 and provides initial conditions for both real-time seasonal forecasts and the calibrating hindcasts. Although only the ocean analyses from 1981 onwards are used directly in S3, the earlier ocean analyses will be used for analysing climate variability, and by the ENSEMBLES project for seasonal and decadal forecasts.

As for S2, the ocean data assimilation system for S3 is based on HOPE-OI (i.e. the optimum interpolation scheme developed for the Hamburg Ocean Primitive Equation model), but major upgrades have been introduced. In addition to subsurface temperature, the optimum interpolation (OI) scheme now assimilates altimeter derived sea-level anomalies and salinity data. There is also a multivariate bias-correction algorithm consisting of a prescribed a priori correction to temperature, salinity and pressure gradient, as well as a time-dependent bias term estimated on-line. The on-line bias correction is adaptive and allows for flow-dependent errors. Because of the a priori bias-correction term, the subsurface relaxation to climatology has been weakened, from a time scale of 18 months in S2 to 10 years in S3. Due to the large uncertainties in the fresh water flux, the relaxation to climatology is stronger for surface salinity (approximately 3-year time scale), but still weaker than in S2 (approximately 6 months).

In order to obtain a first-guess as input to the OI analysis, it is necessary to force the ocean model with atmospheric fluxes. From January 1959 to June 2002 these are taken from ERA-40, and from the ECMWF operational NWP analysis thereafter.

Experiments show that data assimilation gives significant improvements in the representation of the mean state and variability of the upper ocean heat content, when compared to a wind forced ocean model run. In the model's Equatorial Pacific, assimilation steepens the thermocline and increases the amplitude of the interannual variability. In the Indian Ocean it sharpens the thermocline, making it shallower, and increases both the ENSO-related and Indian Dipole variability. In the Equatorial Atlantic assimilation makes the cold phase of the seasonal cycle more pronounced, and the amplitude of the interannual variability is increased.

The improvements that assimilation makes to the ocean initial conditions have a beneficial impact on the seasonal forecasts nearly everywhere, but especially in the west Pacific. A region where there is little impact is the equatorial Atlantic.

Additional experiments have shown that the Argo array has a large impact on the analysed salinity field on a global scale, and leads to improved seasonal forecast skill (Balmaseda et al, 2007). A fuller description of the ocean analysis system can be found in Balmaseda et al. (2006).

3. Assessment of forecast skill

The starting point for a seasonal forecasting system is its skill in predicting sea surface temperature (SST). Comparing anomaly correlation and rms errors in forecasts of Nino 3, Nino 3.4 and Nino 4 SST from S3 with those from S1 and S2 shows clear progress. For example, Figure 1 shows the rms error for the Nino 3.4 index in S3 compared to the earlier operational versions S1 and S2. Over the last decade there has been sustained improvement in the ENSO forecast skill of our operational systems, although estimates of the predictability limit (not shown) suggest that there is still considerable scope for improvement. Scatter diagrams indicate that the improvements in S3 over earlier systems are significant in all areas of the tropical Pacific. However, the strong improvement does not extend to all parts of the globe – outside the equatorial Pacific, changes in SST forecast skill are largely close to neutral, although there is a clear positive benefit in the north subtropical Atlantic.

The quantities that are most commonly wanted from seasonal forecast systems are predictions of near-surface temperature and rainfall. Model-derived forecasts are probabilistic, and should be verified as such. However, to assess which regions have significant predictable signals and how well the model handles them, simple measures such as anomaly correlation are just as effective. Figure 2 (cover page) shows the anomaly correlation for area-averaged seasonal rainfall anomalies in selected regions of the world. The upper panels show the correlation between forecasts and observations - in some regions this is quite high, in others it is near zero. The lower panels show the model estimate of the correlation that would be obtained with a perfect model. The level of potential predictability is in most places a lot higher than the skill presently achieved.

Another view of the adequacy of the model predictions is to look at the reliability diagrams (Figure 3). Here we look at sets of predictions of specific events (eg DJF 2m temperature at a gridpoint exceeding the upper tercile of the model climate), and compare the frequency of the observed outcome to the forecast probability. What we would like to see is a set of points lying on the diagonal, which would indicate that the forecast probabilities are reliable (at least when averaged across the chosen set of events). What we actually see is that temperature forecasts over land are only moderately reliable, and rainfall forecasts over land, while being better than climatology, typically have fairly low reliability. Figure 2 reminds us that this "average low" reliability is made up from quite a spatially diverse signal.

As well as assessing the skill of S3 seasonal forecasts, it is useful to know how the skill has evolved as we have "improved" our seasonal forecast systems. Such an analysis has been made using ROC area scores based on probabilistic forecasts of upper and lower terciles. The results (not shown) indicate that S3 is clearly improved in the tropics relative to S2. The situation in the mid-latitudes is less clear: NH scores over land appear to be slightly better in summer, but slightly worse in winter. Moreover, it seems that the strength of ENSO teleconnections to mid-latitudes is weaker in the model than in observations.

Overall, forecast skill of atmospheric parameters does not demonstrate the clear progress that has been seen in El Nino forecast skill over the last ten years. Errors in the atmosphere models are still causing significant problems in our attempts to build reliable and capable seasonal forecasting systems.

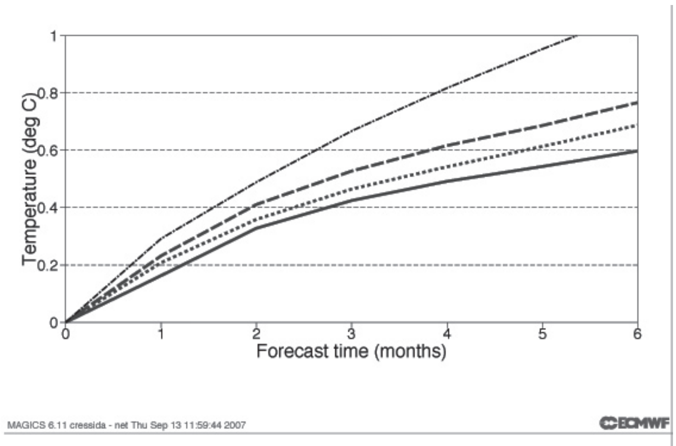

Figure 1: RMS errors for Nino 3.4 SST forecasts from System 1 (dashed), System 2 (dotted) and System 3 (solid), for 192 forecasts in the common period 1987-2002. Results are for 5 member ensembles in each case. For reference, the upper dot-dash line shows the RMS error of persistence of anomalies.

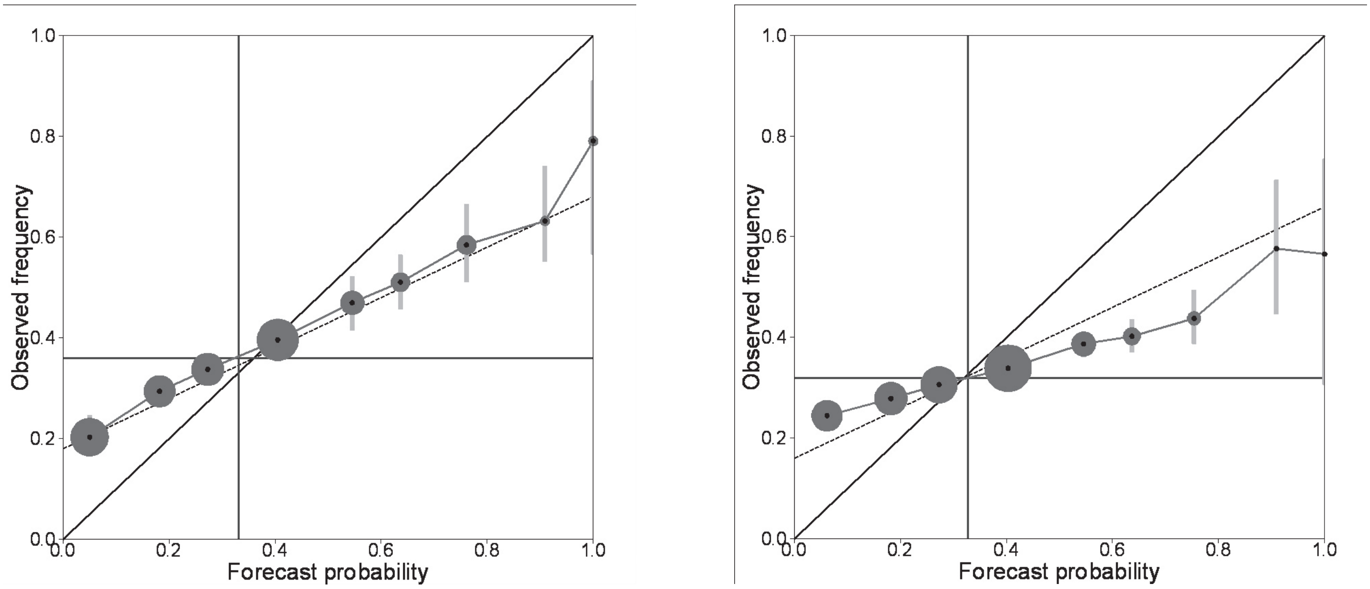

Figure 3: Reliability diagrams for S3 seasonal forecasts, calculated globally for land points only. Reliability of DJF 2m temperature exceeding upper tercile (left) and of JJA precipitation below the lower tercile (right). The size of the circles represents the number of occurrences in each bin, and the error bars are estimated via a bootstrap method. Figures calculated using 1981-2005 hindcasts started from 1 November and 1 May respectively.

4. Forecast products

A set of real-time forecast products is released to the public on the ECMWF website at 12Z on the 22nd of each month - look for the "seasonal forecast" section under www.ecmwf.int/products/forecasts. S3 now includes "tercile summary" plots which show, in a single plot, probabilities of the most likely tercile category if (a) it is one of the outer categories (above upper tercile or below lower tercile) and (b) the probability of the category exceeds 40%. Wider sets of products are available to European and WMO Met Services, and these now include "climagrams", which show in graphical form the predicted evolution of the pdf of area-averaged quantities on a month by month basis. A fuller description of the new seasonal forecast products is available in Molteni et al 2007.

5. Multi-model forecasts

S3 is part of the EUROSIP multi-model seasonal forecasting system. Currently, the participants in EUROSIP are ECMWF, the Met Office and Météo-France, but other members are expected to join in the future. A common operational schedule is followed, and data is held in a common archive at ECMWF, which facilitates production of multi-model forecast products.

6. Summary

Throughout the extensive development period of System 3 various atmospheric model cycles were tested as they became available. Progress was not monotonic. Although each cycle improved or was at least neutral for the medium-range forecasts this was not so for the seasonal forecast range, where new cycles sometimes led to a significant drop in skill. However, the last few cycles have resulted in strong and significant gains in SST prediction skill, and the model version used in System 3 is the best yet seen when assessed by its ability to predict El Nino SST variations in the Pacific.

System 3 still has clear deficiencies, however. Blocking in the northern hemisphere is not well handled, and the Madden-Julian Oscillation (MJO) is not well represented. Improvements in blocking and the MJO would be beneficial to 15 day and monthly forecasts as well as to the seasonal range. Since the coupled ocean-atmosphere model is now well integrated into the ECMWF research and operational systems, it is possible to test model changes across a range of timescales at an early stage of the model development cycle. ECMWF strategy is to have a single model version which works well at all timescales from the data assimilation cycle (hours) to seasonal.

Several other major features of System 3 should be highlighted. The ocean analysis/reanalysis is a major product in its own right. The increased ensemble size and the larger set of back integrations (25 years rather than 15 years) increase the accuracy of the forecast products. This is a big step forward for those wishing to process the model output themselves to create tailored seasonal forecast products. The new experimental ENSO outlook forecasts extending to 13 months give a longer-range outlook on one of the major factors that drives seasonal climate anomalies. There is still scope for substantial improvements in the future, but we hope that System 3 will be a useful step on the road to developing numerical systems that fully exploit the predictability that exists on seasonal timescales.

Acknowledgements

The ECMWF seasonal forecast System 3 is the result of a team effort, involving the listed authors (the main development team) and many other members of the ECMWF research and operations departments.

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An assessment of cross validation for estimating skill of empirical seasonal forecasts using a global coupled model simulation

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1. Introduction

Most empirical forecasting techniques suffer because of the relative shortness of historical data on which prediction models are based and their predictive skill is evaluated. The problem is aggravated by the fact that historical records are used both for developing a statistical prediction model and for evaluating its performance. Ideally, the validation of the predictive skill of an empirical method should only be based on data that follow the "training datasets" used to develop the statistical model. No information from the validation stage should "leak" into the model development stage to avoid introduction of artificial skill.

Given the relatively short historical record of climate data, it is often difficult to fulfill these requirements in practice. On the one hand, it is desirable to devise a prediction scheme that reliably captures fundamental relationships between predictors and response variables and minimizes extraneous information related to sampling variability and measurement errors. This demands that the datasets used are those that employ the longest training periods available. On the other hand, the validation period should be long enough to reliably evaluate the performance of the predictive model.

Cross validation is a standard approach to accommodate the two conflicting requirements and to use available historical records more efficiently. The assumption is that cross validation will simulate actual forecast situations without relying on past coincidences that are unlikely to be repeated into the future. However, cross validation has a potential to exaggerate the true predictive skill of a statistical model when some of the assumptions of cross validating techniques are compromised. Elsner and Schmertmann (1994) outline some of the pitfalls of cross validation that must be avoided and various approaches to mitigate them. These include the avoidance of the forecast target data in the development of the prediction algorithm at all stages, and the omission of a single observation in the cross validation procedure. The latter may introduce bias into the estimation of forecast skill. In the presence of serial correlation in climate noise, the removal of a single observation should be replaced by the removal of blocks of observations. Michaelsen (1987) further outlines the method of cross validation, as well as the issues related to its successful implementation for a regression model. The main purpose of this study is to evaluate the possible artificial skill enhancement for seasonal temperature forecasts over Canada based on the Canonical Correlation Analysis (CCA) statistical forecasting model, which is described in more detail in section 2.1.

Given the limited historical record this objective can hardly be achieved using the observed data. Instead, we use model output from a multi-century control simulation with the coupled general circulation model (CGCM2) of the Canadian Climate Centre and Modelling Analysis (CCCma). The long simulation allows us to assess the reliability of the CCA statistical forecasting model. The caveat of a model-output based study is that due to model deficiencies the model-simulated coupled variability and relationships may not be an accurate reflection of the observed. In particular, CGCM2 is known for under simulating the amplitude of the El Niño-Southern Oscillation (ENSO) variability (Yu and Boer 2002) which is thought to be the main source of skill on seasonal to annual time scales in North America (e.g. Higgins et al. 2000). Therefore, the overall skill level in the model simulation may not be an accurate indication of the true observed skill. Yet we expect that this approach will provide useful information about the reliability of the in-sample skill score estimates of the operational CCA seasonal forecasts as compared to the true out-of-sample predictive skill.

2. Experiment setup

2.1 The CCA

Utilizing a specific variation of the empirical orthogonal function (EOF) analysis (Barnett and Preisendorfer 1987), the empirical CCA technique models linear relationships between fields of the predictors and fields of predictands. The forecasts are made based on the co-variability between predictors and predictand during the training period. Specifically, CCA performs a multivariate linear regression so that patterns in predictand field are related to preceding four seasons' patterns in predictor fields. One of the important predictors for the Canadian surface air temperature is the global sea surface temperature (SST) field (Shabbar and Barnston 1996). Further details concerning the CCA methodology is described in Barnston and Smith (1996). Presently, CCA constitutes a component of seasonal forecasting methodology at the forecasting centres in both Canada and the United States.

In the "in-sample" experiments, cross validation is used for skill assessment. All data for the prediction year are withheld, and the CCA model is developed based on the remaining sample. Calculations of all statistics, i.e., mean, standard deviation, EOF and CCA modes, are repeated for each of the withheld prediction year, and the process is repeated until predictions are made for each year in the sample. It is believed that the strong trend in the SSTs may produce inflated skill in a leave-one-out cross validation scheme. In this work, therefore, we also perform cross validation by withholding three and five years from the training sample. Cross validated skill score estimates are compared with skill estimated from independent samples.

2.2 CGCM2 and CCA experiment design

Both the predictor (global SSTs) and the predictand (surface temperature as 2 m temperatures over Canada) are from a multi-century climate simulation with CGCM2. Briefly, CGCM2 consists of the CCCma second-generation atmospheric circulation model (McFarlane et al. 1992) coupled to a GFDL modular ocean model (MOM1). The atmospheric component is a global spectral model with T32L10 resolution. The ocean model has a resolution of 1.8 degree x 1.8 degree in horizontal and 29 levels in vertical. Further details of the model are given in Flato et al. (2000). The control simulation is performed with constant atmospheric composition and external forcing. It is found that variability over land is well simulated; however, variability over tropical oceans is generally underestimated. This very long and stable climate simulation provides an opportunity to assess reliability of the CCA forecast skill estimation using cross validation and on independent samples.

A number of experiments are devised in order to compare cross-validated and out-of-sample skill score estimates. Cross-validated skill scores are obtained for 14 non-overlapping 50-year periods. In the following we will also refer to cross-validated estimates as in-sample estimates to emphasize that they are based on the same training period and may be subject to artificial skill inflation. Out-of-sample estimates are obtained for 18 non-overlapping 50-year periods. In these "out-of-sample" experiments, a CCA model is developed on a 50-year period and forecasts are constructed and evaluated on the following 50-year period. Out-of-sample skill estimates provide a more fair assessment of the forecasting model performance. Forecasts are made for four standard climatological seasons (Dec-Feb, Mar-May, Jun-Aug, Sep-Nov), and for four leads (0, 3, 6 and 9 months). Cross validation is performed by withholding 1, 3 and 5 years in the CCA model development, and the forecast is verified on the first of the withheld years.

The performance of deterministic CCA forecasts is evaluated using two skill measures, the percent correct score of the three equi-probable classes of above-normal, near-normal and below-normal, and the anomaly correlation coefficient. When evaluating out-of-sample skill, anomalies in the forecast 50 year period are constructed using the time mean of the training period. Additionally, the definition of three classes for the percent correct is based on the training period data. Average skill and spread (variability) are highlighted for both in-sample cross-validated forecasts and out-of-sample forecasts.

3. Results

3.1 Percent correct

The percent correct score is a measure of deterministic categorical forecast skill. It is defined as the fraction of correctly predicted equi-probable categories to the total number of categorical forecasts. Percent correct of random forecasts is 33.3%. Figure 1 shows box-plot summaries of percent correct scores averaged over Canada for zero-lead seasonal forecasts

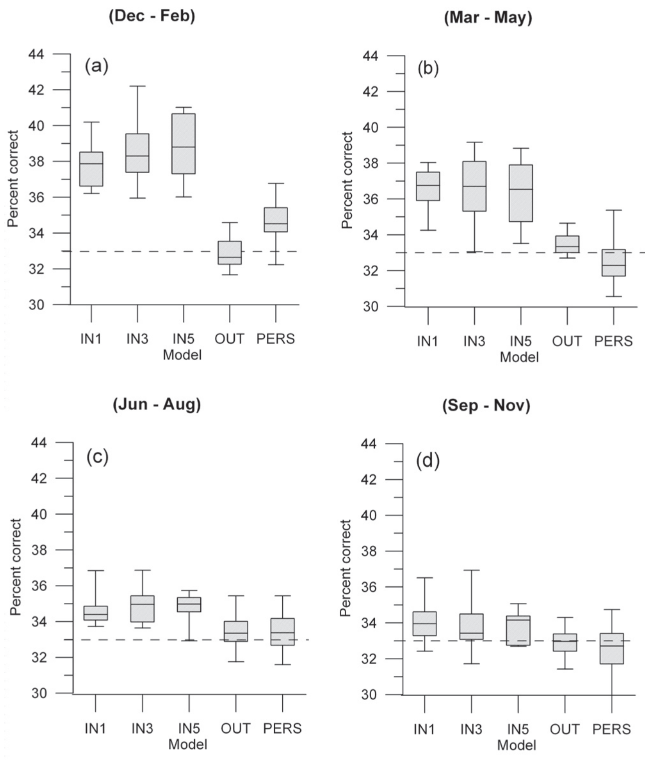

Figure 1: Boxplot summaries (the smallest value, lower quartile, median, upper quartile, and largest value) of percent correct skill scores of zero-lead forecasts of Canadian surface air temperature for four seasons (a) December-February, (b) March-May, (c) June-August, and (d) September-November. Cross-validated in-sample skill score estimates withholding 1, 3, and 5 years out of sample are denoted by IN1, IN3, and IN5, respectively. Out-of-sample skill score estimates are denoted by OUT. Skill scores of persistency forecasts are denoted by PERS.

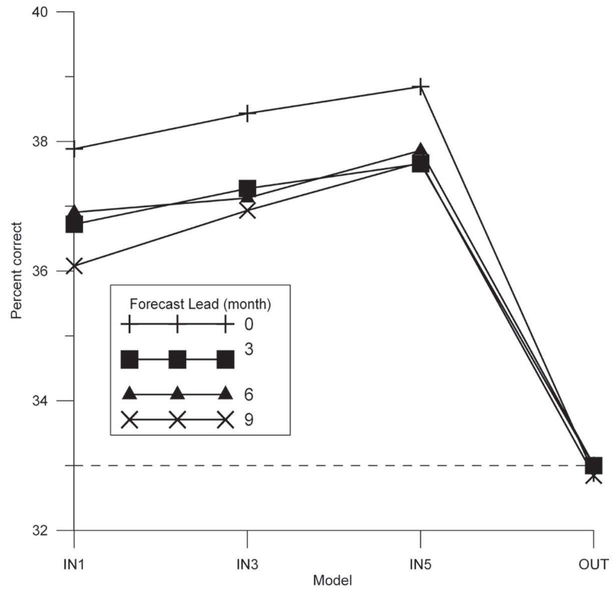

Figure 2: The average percent correct skill score of December-February Canadian surface air temperature forecasts for 0-, 3-, 6-, and 9-month leads. Cross-validated in-sample skill score estimates withholding 1, 3, and 5 years out of sample are denoted by IN1, IN3, and IN5, respectively. Out-of-sample skill score estimates are denoted by OUT.

of Canadian surface air temperature based on 14 in-sample, 18 out-of-sample 50-year models as well as for corresponding persistence forecasts. A box-plot indicates the smallest value, lower quartile, median, upper quartile, and largest value in a sample. Summaries of in-sample estimates obtained in cross validation by withholding 1, 3, and 5 years are indicated by IN1, IN3 and IN5 respectively. Skill scores that are based on cross-validated forecast scores are consistently higher than those based on out-of-sample forecasts during the cold seasons (Figs. 1a and 1b). The out-of-sample scores are significantly lower than in-sample scores and indistinguishable from zero-skill forecast score of 33.3%. Skill scores from persistence forecasts also show little skill. During Jun-Aug (Fig.1c) and Sep-Nov (Fig. 1d), the median scores from in-sample, out-of-sample and persistence forecasts show no skill. Additionally, variability within each sample is somewhat smaller.

Skill scores of Dec-Feb forecasts for different time leads are shown in Figure 2. There is a degradation of in-sample average scores as the lead time is increased from zero to nine months. Average out-of-sample scores are no better than 33.3%, and persistence forecast scores are only slightly better than out-of-sample scores. Somewhat surprising is the finding that cross-validated skill scores do not decrease with withdrawing more years from the training period. Overall, all in-sample cross validated skill score estimates are considerably higher than out-of-sample scores.

3.2 Anomaly correlation

The anomaly correlation coefficient is a measure of deterministic specific value forecasts and is defined as:

$$AC = \frac{\sum_i (x_{f_i} - \overline{x}_f)(x_{o_i} - \overline{x}_o)}{\left\{ \sum_i (x_{f_i} - \overline{x}_f)^2 \sum_i (x_{o_i} - \overline{x}_o)^2 \right\}^{1/2}}$$

where subscript f and o refer to the forecast and observed data respectively and the overbar refers to the time mean at

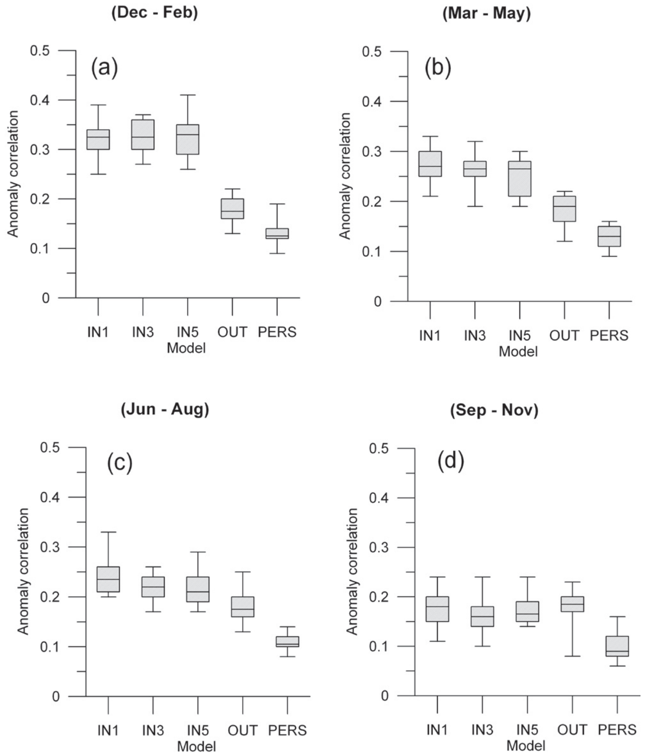

Figure 3: The same as Figure 1 but for the anomaly correlation skill score.

location i. Anomaly correlation coefficients are calculated for each grid location in Canada and then spatially averaged. Figure 3 displays boxplot summaries of the averaged anomaly correlation scores of zero lead seasonal forecasts based on 14 in-sample and 18 out-of-sample models. Similar to the percent correct scores (Fig.1), in-sample AC are considerably higher than out-of-sample AC in the cold seasons (Figs 3a and 3b). Both the scores and their variability remain the same in the in-sample group in the Dec-Feb season. Scores from persistence forecasts have a median value of near 0.15. During Mar-May, in-sample scores remain appreciably higher than out-of-sample and persistence forecast scores. The AC scores in Jun-Aug (Fig. 3c) and Sep-Nov (Fig. 3d) are markedly low in all four models.

Figure 4 shows the Dec-Feb average anomaly correlation scores at various lead times. The in-sample skill scores are the highest for zero lead but of similar magnitude for other leads. Out-of sample skill scores of CCA forecasts, however, show a precipitous drop and become comparable to the skill of persistency forecasts (not shown).

4. Concluding remarks

A 1000-year control simulation of CGCM2 is employed to assess the reliability of skill score estimates of CCA-based seasonal forecasts in Canada. This evaluation is done for the CCA model that uses global SSTs as predictor for Canadian surface air temperature. Cross-validated skill score estimates are obtained in cross validation with 1, 3 and 5 years out. These in-sample skill scores are compared to the out-of-sample skill estimates obtained on independent samples. The inter-comparison is performed for standard seasons and for a number of lead times. Since the overall skill level in the CGCM2 simulation may not be an accurate indication of the true observed skill due to deficiencies in simulating the ENSO variability, the absolute values of skill scores considered here may not reflect the true capability of the CCA model in practice. Nevertheless, the performed experiments are able to highlight the differences between skill score estimates obtained in cross-validation and based on independent samples.

Results of this study show that the skill estimates of CCA seasonal forecasts obtained through the cross-validation technique are severely inflated. The in-sample cross-validated skill estimates are consistently higher then out-of-sample skill estimates at all lead times. Moreover, the skill inflation does not decrease when more than one year are withdrawn in cross-validation. It is suggested that using cross validation techniques to assess performance of operational CCA seasonal forecasts may also overestimate the true level of skill.

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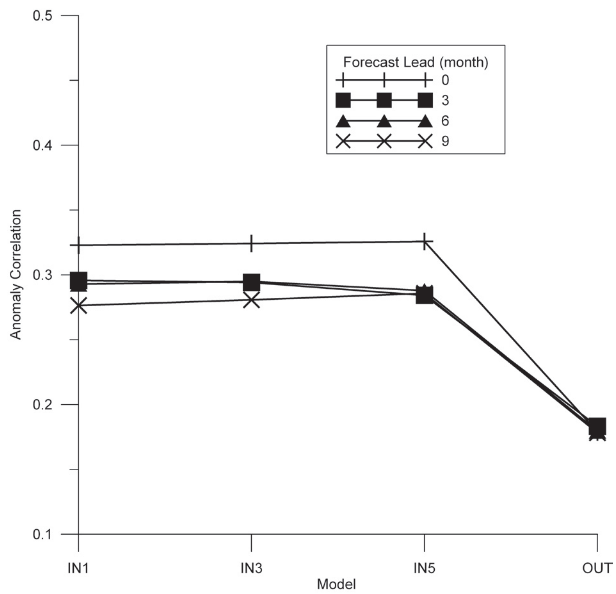

Figure 4: The same as Figure 2 but for the anomaly correlation skill score.

Integrated seasonal climate forecasts for South America

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Introduction

Seasonal climate forecasts for South America are currently produced using empirical (statistical) and dynamical (physical) models. Given the availability of these two modelling approaches one might question the feasibility of producing a single and well calibrated integrated forecast that gathers all available information at the time the forecast is issued. This study illustrates how empirical and dynamical coupled model seasonal forecasts of precipitation for South America are currently being integrated (i.e. combined and calibrated) in EUROBRISA (A EURO-BRazilian Initiative for improving South American seasonal forecasts, http://www.cptec.inpe.br/~caio/EUROBRISA). The skill of one month lead austral winter (June-July-August) forecasts is assessed and discussed.

Methodology

One of the simplest empirical approaches to produce one-month lead austral winter (June-July-August) South America precipitation forecasts is to use, as predictor variable, Pacific and Atlantic sea surface temperatures observed in the previous April. This multivariate regression model (Coelho et al. 2006) is used here to produce empirical precipitation forecasts for South America.

The dynamical systems used in this study to produce one-month lead precipitation forecasts for June-July-August are the coupled ocean-atmosphere seasonal prediction models of ECMWF (Anderson et al. 2007), known as System 3, and the UK Met Office (UKMO; Graham et al. 2005), known as GloSea. The forecast output from these models is coordinated at ECMWF as part of the European Seasonal to Inter-annual Prediction project (EUROSIP).

To produce empirical-dynamical multi-model integrated probabilistic forecasts we apply a Bayesian procedure, known as forecast assimilation (Stephenson et al. 2005). This procedure allows the spatial calibration and combination of forecasts produced by each individual model. The skill of empirical, ECMWF, UKMO and integrated forecasts obtained with forecast assimilation is assessed and compared over the common hindcast period 1987-2001. All results were obtained using the cross-validation method (Wilks 1995). Forecast verification is performed using the version 2 Global Precipitation Climatology Project (GPCP) monthly precipitation analysis (Adler et al. 2003).

Results and discussion

Figure 1a-d (page 19) shows correlation maps of ECMWF, UKMO, empirical and integrated precipitation anomaly forecasts for the period 1987–2001. Correlation maps show the correlation between observed and mean forecast anomalies at each grid point. Both ECMWF and UKMO forecasts are bias corrected because we are dealing with ensemble mean forecast anomalies with respect to each model climatology. The three individual models show high skill with correlation coefficients generally between 0.4 and 0.8 in tropical South America. ECMWF, UKMO and empirical forecasts are moderately skilful over the south of Brazil and southeast Argentina with correlation coefficients between 0.2 and 0.6. Empirical forecasts also show moderate skill over Bolivia with correlation coefficients between 0.4 and 0.6. When the forecasts of the three individual models were combined and calibrated to produce integrated forecasts, improved skill was obtained over tropical and southeast South America (Fig. 1d).

Correlation is a deterministic measure of skill that indicates how well associated the forecast is with the corresponding observed anomaly. Correlation, however, only assesses the mean forecast value. In order to assess how well forecast uncertainty is estimated, one needs for example to examine probabilistic scores. Here we examine Gerrity (1992) score maps for tercile probability categories (Figs 1e-h, page 19). Tercile categories are defined as below normal, normal and above normal according to the climatological June-July-August precipitation distribution. Large values of Gerrity score indicate increasing correspondence between the category that was forecast as most likely and the category that was observed. In accordance with the correlation map (Fig 1d), integrated forecasts (Fig 1h) have

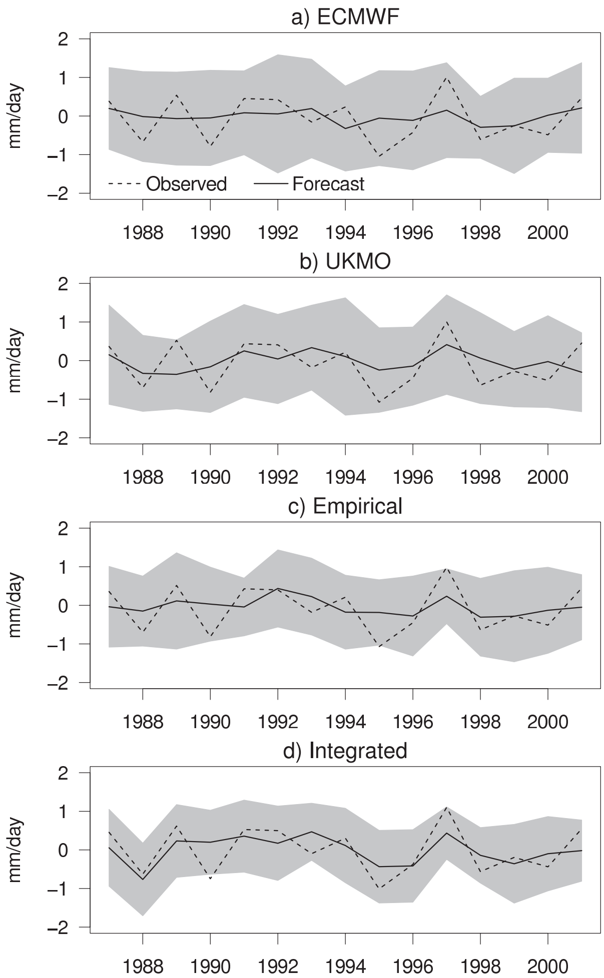

Figure 2: One-month lead June-July-August 1987–2001 precipitation anomaly forecasts (mm/day) for a grid point in southeast South America (longitude 297.5°; latitude -37.5°) produced by a) ECMWF coupled model, b) UKMO coupled model, c) empirical model and d) integrated (combined and calibrated) with forecast assimilation. Observed values (dashed line), forecast (solid line), and the 95% prediction interval (grey shading).

improved (higher) skill in tropical and southeast South America when compared to the three individual forecasts (Figs. 1e-g). This result indicates that not only the estimate of the mean forecast value is improved by calibration and combination of empirical and coupled model forecasts. Uncertainty estimates are also improved by calibration and combination.

Figure 2 shows austral winter 1987–2001 precipitation anomaly forecasts for a grid point in southeast South America (longitude 297.5^o; latitude -37.5^o) produced by ECMWF, UKMO, empirical and integrated (combined and calibrated) with forecast assimilation. The 95% prediction interval (grey shading) is given by the mean forecast value plus or minus 1.96 times the forecast standard deviation. ECMWF and UKMO forecast standard deviation (i.e. the spread) is computed as the standard deviation of the ensemble members of each model. Empirical and integrated forecast standard deviation is computed as described in Coelho et al. (2006) and Stephenson et al. (2005), respectively, and posteriorly re-scaled to match the mean forecast error. Figure 2 shows that all four forecasting approaches produce reliable forecast uncertainty estimates, with most observations falling inside the 95% prediction intervals. ECMWF and UKMO have larger 95% prediction intervals than empirical and integrated forecasts. Integrated forecasts are well calibrated showing the best agreement between the mean forecast value and the observed anomalies (Fig 2d). Integrated forecasts have the largest amount of interannual variability. This is also reflected in the highest correlation between integrated forecast and observed anomalies. The correlation coefficients between forecast and observed anomalies for ECMWF, UKMO, empirical and integrated forecasts are 0.42, 0.44, 0.56 and 0.65, respectively.

Conclusions

This study has examined the skill of austral winter seasonal forecasts for South America produced by two coupled ocean-atmosphere models, an empirical model and integrated (i.e. combined and calibrated) forecasts. The main findings can be summarised as follows:

- forecast skill can be improved by calibration and combination;
- the availability of forecasts produced by both empirical and coupled models provide the opportunity to produce objectively integrated, in other words, combined and well calibrated probabilistic forecasts that gather all available information at the time the forecast is issued;
- austral winter precipitation forecasts produced by the empirical-dynamical multi-model integrated system presented here are skilful in tropical and southeast South America.
- integrated forecasts generally provide skill that is equal to or better than that of the best individual model

Acknowledgments

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LATEST NEWS

We were delighted to hear that the Norwegian Nobel Committee has decided that the Nobel Peace Prize for 2007 is awarded "for efforts to build up and disseminate greater knowledge about man-made climate change, and to lay the foundations for the measures that are needed to counteract such change". The prize is to be shared in two equal parts, between the Intergovernmental Panel on Climate Change (IPCC) and Albert Arnold (Al) Gore Jr. Many WCRP-related scientists are, and have been, involved in IPCC which itself builds on the work of the wider community climate scientists world-wide. Congratulations to both IPCC and Al Gore. Further information is at http://nobelprize.org/

Austral summer precipitation over South America based on SMIP simulations.

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The Seasonal Prediction Model Project (SMIP) provided the opportunity to verify the performance of seasonal simulations using several Atmospheric Global Circulation Models (AGCM's) in several regions of the world, as well as to analyze results from a multi-model ensemble. Three month averaged South American rainfall and temperature have been predicted every month in centers like the IRI, CPTEC/INPE, ECMWF, UK Meteorological Office, using predicted or persisted SSTs in AGCMs or Coupled Atmosphere-Ocean Models. The IRI has applied the multi-model approach using AGCMs from several centers (Barnston et al. 2003). Previous simulations using the CPTEC/COLA AGCM were performed in long-range climate integrations and seasonal results were discussed in Cavalcanti et al. (2002) and Marengo et al. (2003). In SMIP simulations, initial conditions for each year and each season are considered, different from a long-range simulation, which has initial conditions only in the beginning of the integration. Therefore, it is important to investigate if the SMIP (i.e., initialized) approach has an impact on the seasonal results, and also how the other SMIP models simulate South America seasonal features.

In this study, DJF austral summer season is analyzed in SMIP-2 results, which are compared with surface observed precipitation and CMAP/CAMS estimated precipitation. The SMIP models used in the analysis are from CPTEC/INPE (Brazil), SCRIPPS (USA), IAP (China), KMA (Korea) and MGO (Russia) obtained from http://ingrid.ldeo.Columbia/edu/SOURCES/.WRCP/.SMIP-2/overview.html. CPTEC/COLA AGCM shows similar systematic errors to those noticed in previous long-range climate simulations with the same model. Overestimated precipitation occurs over eastern and northeastern Brazil, and underestimated precipitation over Amazonia and southern Brazil. In contrast to our previous experience with long-range climate simulations we find relatively small spread in the seasonal forecast using initial conditions at each season. In the long-range simulation, results considering different initial conditions presented larger dispersion than in the seasonal simulation mode, probably due to the length of integration. The 1st and 2nd season potential predictabilities were evaluated and although the results were very similar for DJF, there was a slight improvement in the 1st season, when compared to the observed surface precipitation (Figure 1 page 19).

The other SMIP models were evaluated considering the ensemble mean of each model for DJF season. SCRIPPS, MGO and KMA show improvements over Amazonia, although SCRIPPS overestimates the rainfall over the whole continent. All the models except IAP show overestimation over the South American Convergence Zone (SACZ), but the Atlantic Inter-Tropical Convergence Zone (ITCZ) is not simulated in the IAP results. A multi-model analysis is performed taking five SMIP models (CPTEC, SCRIPPS, IAP, KMA, MGO) to assess the improvements over a single model. The multi-model ensemble shows a strong improvement reducing the errors noticed in CPTEC/COLA model (Figure 2 page 20). However, if CPTEC/COLA AGCM is removed from the multi-model ensemble, the errors are larger.

In addition, extreme cases of precipitation over Southeastern Brazil in DJF were analyzed in GPCP data and CPTEC model results for 5 members. The range of frequency of observed extreme cases was similar to that simulated by all members, and there are some years when the number of cases were similar to observations (Figure 3). In particular, the frequency of observed cases during the period of 1993 to 1996 was well simulated by one specific member.

Based on SMIP analysis, precipitation simulation over South America improves if a multi-model ensemble is used. Systematic errors considering CMAP/CAMS or surface observations indicated the same regions with overestimated or underestimated values, but, as the model has higher resolution than CMAP/CAMS, the ground observed data interpolated in the model grid shows more details of regional errors. Further analysis considering predicted SSTs in SMIP type simulations are planned in future studies.

Acknowledgments:
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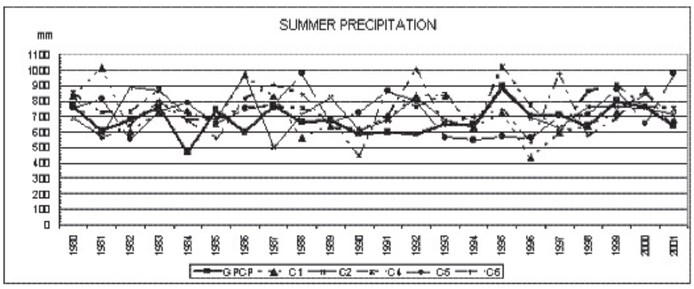

Fig.3. Interannual mean DJF average precipitation (mm) over Southeastern Brazil from GPCP and 5 members of CPTEC/COLA AGCM SMIP data set.

Do seasonal forecasts reproduce the link between early and peak monsoon rainfall in South America?

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Previous observational studies (Grimm et al. 2007) have disclosed a link between peak summer monsoon rainfall in Central-East Brazil, comprising part of the South American monsoon core region, and antecedent conditions in spring. Rainfall in this region during part of spring shows significant inverse correlation with rainfall in peak summer, especially during ENSO years. The corresponding precipitation anomalies appear in the first modes of spring and summer variability for South America. A surface-atmosphere feedback hypothesis involving soil moisture in spring has been proposed to explain this relationship, and a crucial role of the mountains in Central-East Brazil is suggested by modeling experiments (Grimm et al. 2007). Low spring precipitation leads to low spring soil moisture and high late spring surface temperature in that region; this induces a topographically-enhanced low-level anomalous convergence and cyclonic circulation over Southeast Brazil that enhances the moisture flux from northern and central South America into Central-East Brazil, setting up favorable conditions for excess rainfall (Figure. 1a page 20). Antecedent wet conditions in spring lead to opposite anomalies. The temperature anomalies in the southern part of Central-East Brazil seem to be the most related to the precipitation over the entire region in peak summer.

There has not been any assessment of climate models' ability in reproducing this relationship between early and peak summer monsoon rainfall in South America. Central-East Brazil is one of the regions of South America in which the seasonal forecasts for austral summer precipitation (DJF) have no skill, according to the average performance of 11 models (Cavalcanti et al., 2006). Such an assessment could shed some light on the reasons for this bad performance. Therefore, we analyze austral spring/summer seasonal forecasts with focus on the interannual variability and on the relationship between the spring conditions and the summer forecast.

Output from the CPTEC/COLA AGCM seasonal simulations for the SMIP2 project are used in the analysis. This spectral atmospheric model was integrated with T62L28 resolution for the SMIP2 period (1979 to 2001), applying observed SST as boundary conditions. The model is run each year for four overlapping seasons, considering simulations of six months. In this study, the ensemble mean of five simulations for SONDJF will be analyzed.

The two first observed modes of spring (SON) precipitation both present anomalies over Central-East Brazil: in the first mode they are concentrated in the southern part of this region, while in the second mode they spread over the entire region (Figure. 1b page 20, upper left panels). In summer, there are also precipitation anomalies over Central-East Brazil in both first modes (Figure. 1b, bottom left panels). The spring and summer second modes are the most affected by ENSO. Significant correlation exists between the first spring and summer modes, as well as between the second modes (indicated by the blue arrows and numbers in the left panels of Figure. 1b). In agreement with the inverse relationship between spring and summer precipitation in Central-East Brazil, these correlations indicate that a precipitation anomaly in this region in spring tends to be followed by an opposite anomaly in summer.

The first and second observed modes for spring (Figure. 1b, upper left panels) are both significantly correlated with the first spring mode from the model (Figure. 1b, upper right panel; correlations are indicated by red arrows and numbers). Likewise, the first and second observed modes for summer (Figure. 1b, bottom left panels) are significantly correlated with the first summer mode produced by the model (Figure. 1b, bottom right panel). Both for spring and summer, the correlation is strongest with the second observed mode, which is ENSO-related. The model is not able to reproduce the differences between the first and second observed modes, at least not through modes that explain comparable variance, and therefore its first mode explains a much higher fraction of the variance than the first observed mode, both for spring and summer. In spite of the exaggerated response of the model to ENSO, it does not represent certain important characteristics of the observed spatial distribution of the precipitation anomalies, which are important for the spring-summer relationship in Central-East Brazil. It shows a dipole-like structure with opposite anomalies in central-northern and southeastern South America, both in spring and summer, and does not reproduce the strong precipitation anomalies in Central-East Brazil in spring present in the observed mode. This might be ascribed to the incomplete simulation of ENSO teleconnections over South America, especially over Central-East Brazil.

If the spring precipitation anomalies in Central-East Brazil are not well represented, then the relationship between spring and summer precipitation cannot be reproduced. The correlation between the first spring and summer modes from the model is negative (as indicated in Figure. 1b, right panels), which means that the model tends to produce anomalies of the same sign in spring and summer in most of this region. The tendency to changing sign prevails in the observed modes.

It is not possible to say that the model does not reproduce the inverse relationship between precipitation in Central-East Brazil in spring and summer, as the precipitation in spring is not well simulated in this region, and therefore cannot trigger the processes that lead to reverse precipitation anomalies in peak summer. The analysis of one of the members of the ensemble (not shown) suggests that this relationship would be reproduced provided that the precipitation anomalies over Central-East Brazil in spring are correctly represented.

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Coupled Predictability of Seasonal Tropical Precipitation

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Introduction
Prediction of seasonal-to-interannual climate variations and the associated uncertainties using multiple coupled models has become operational. However, how to determine the practical predictability of the tropical seasonal precipitation in coupled climate models remains an unresolved issue. We propose and compare two methods. The first relies on identification of the "predictable" leading modes of the interannual variations in observations and multi-model ensemble (MME) hindcast results. The predictability is quantified by the fractional variance accounted for by the "predictable" leading modes. The second approach is based on the signal to noise ratio, which extends the method used for assessing the predictability in atmospheric general circulation models for given lower boundary forcing (e.g., Kang and Shukla 2006). Here the signal is measured by the MME mean, while the noise is measured by the "spread" among individual model's ensemble means. We demonstrate the conceptual consistency and differences between the two measures of predictability using 10 coupled climate prediction models.

Data and analysis procedure
The models that are examined in this study are 10 fully coupled atmosphere-ocean-land seasonal prediction systems that come from the following two international projects: the Development of a European Multi-model Ensemble system for seasonal to inTERannual prediction (DEMETER) (Palmer et al. 2004) and the Asia-Pacific Economic Cooperation Climate Center/Climate Prediction and Its Application to Society (APCC/CliPAS) (Wang et al. 2007).

The selected models have retrospective forecasts (hindcasts) for the common 21-year period of 1981-2001 with 6- to 9-month integrations for 6 to 15 different initial conditions for four seasons. The hindcasts are initialized in February 1, May 1, August 1, and November 1. We use one-month lead seasonal forecasts of precipitation for four seasons. Suppose the forecast was initialized on February 1, the one-month lead seasonal prediction means the average of predicted March, April, and May means. The Climate Prediction Center Merged Analysis of Precipitation (CMAP) data set (Xie and Arkin 1997) is used as the verification dataset.

Season-reliant Empirical Orthogonal Function (S-EOF) analysis (Wang and An 2005; Wang et al 2007) was applied to seasonal precipitation over the Tropics from 30°S to 30°N in order to identify the "predictable" leading modes of interannual variations of tropical precipitation. The purpose of the S-EOF is to depict seasonally evolving anomalies throughout a full monsoon calendar year. A covariance matrix was constructed using four consecutive seasonal mean anomalies for JJA(0), SON(0), DJF(0/1), and MAM(1) that were treated as a "yearly block". Here Year 0 refers to the year in which the sequence of anomalies commences.

Results
Figure 1 (page 20) shows the performance of the coupled MME system on one-month lead seasonal prediction in terms of temporal correlation skill over the entire Tropics for 21 years from 1981 to 2001. The correlation coefficients that are higher than 0.5 are generally observed over the tropical Pacific and Atlantic between 10°S and 20°N all year around. Prediction in DJF, SON and MAM is evidently better than JJA due to the model's capacity in capturing the ENSO teleconnections around the mature phases of ENSO. In JJA, while the skill increases over the North Pacific and North Atlantic due to northward migration of the thermal equator, the skill over the Indian Ocean and the continental summer monsoon regions are very low. The correlation skill in the Asian-Australian monsoon (A-AM) region remains moderate, varying from 0.3 to 0.5 depending on season.

We found that the MME prediction skill of the seasonal tropical precipitation basically comes from the first four leading modes of S-EOF. The fractional variance is obtained from the ratio of the variance associated with a single S-EOF mode to the total variance (Wang and An 2005). The first four leading modes of precipitation in observations account for about 60% of the total variances. The first two S-EOF modes are very well predicted in terms of both the spatial structure and temporal evolution (Figure 2). The third and even the fourth modes are also reasonably well predicted. But all other higher modes are not predictable as shown by the insignificant correlation skills in the spatial structures (Figure 2). Thus, we consider the first four major modes as the predictable part of the interannual variations.

Figure 3a and b (page 20) show the fractional variance explained by the predictable leading modes for all seasons in observations and MME prediction, respectively. In observations, the fractional variance exhibits large spatial variations. Those predictable modes are significantly related to ENSO variability with different lead-lag relationships, especially the 1st and 2nd modes (not shown). The MME prediction exaggerates the

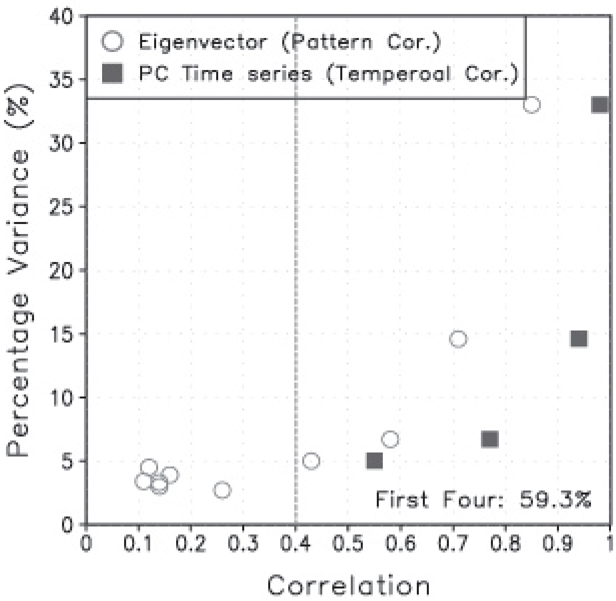

Figure 2: The spatial pattern correlation (circle) of eigen vector and temporal correlation (filled square) of principal component time series between the observed and predicted S-EOF modes for precipitation over the globe [0-360E, 30S-40N]. The first four major modes of observed seasonal precipitation over the tropics capture total 60% of the variability.

fractional variance of predictable modes (Figure 3), suggesting that the MME does not capture the higher modes.

How good is the prediction skill of the MME in terms of the predictable part? Figure 3d shows correlation skill for reconstructed precipitation by only using the four predictable modes. The similarity between Figures. 3c and 3d indicates that the MME prediction skill basically comes from the first four leading modes of seasonal precipitation.

Conclusion

How to measure the predictability of the coupled climate system, where no atmospheric lower boundary forcing is given, is an open issue. We have shown that the prediction skill of the coupled model MME basically comes from the skill in prediction of the first four major modes of interannual variations in the global tropical precipitation (Figures 3c and d). The four modes together account for about 60% of the total interannual variance averaged over the Tropics in observations (Figure 2). This portion of the variation may be considered as the practically predictable part of the precipitation variability, because the MME can capture these four major modes reasonably well but cannot capture the rest of the higher modes (Figure 2). This result leads to a new approach to estimate the practical predictability of the tropical seasonal precipitation in coupled climate models; i.e., we can quantify the "predictability" by the fractional variance that is accounted for by the "predictable" leading modes in the observations (the left panels of Figure 4, page 21)). Such "predictable" modes can be determined by examining models' hindcast results such as the performance shown in Figure 2.

The second possible approach is to extend the idea of signal-to-noise ratio used for assessing the atmospheric predictability for a given lower boundary forcing. In coupled models, the signal may be measured by the interannual variation of the MME, while the noise is measured by the "spread" (variance) among individual model's ensemble mean. In this measure the region in which the spreading exceeds the interannual variation of MME is considered as unpredictable. It is found that the signal-to-noise ratio defined as above may underestimate the models' predictability over the Western North Pacific in JJA and SON and over Maritime Continent in DJF and MAM (right panel in Figure 4). While the models' predictions have a large spread compared to the interannual variations in MME in the aforementioned regions, the hindcast results indicate that the MME does have practically useful skills there (Figure 1). In contrast, there is spatial consistency between the fractional variance of observed "predictable" modes and MME hindcast skill. The concept and approach proposed here is preliminary and more in-depth research is underway.

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Asian Monsoon Predictability in JMA/MRI Seasonal Forecast System

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1. Introduction

The Japan Meteorological Agency (JMA) has been running a forecast system for ENSO using a coupled atmosphere-ocean model since 1999. The JMA also operates the TL95L40 atmosphere general circulation model (AGCM) in a two-tiered mode for seasonal forecasts. The persistent SST anomalies at initial time are prescribed for one-month-lead 3-month forecasts.

One reason for the use of the two-tiered forecast system is that the JMA one-month-lead forecast system shows relatively good skill over Japan after statistical downscaling is applied: correlations of 0.6 (0.47) in the boreal summer (winter) are obtained in hindcast mode. Good reliability is also found in the real time operational forecast (not shown here). The good forecast skill may be partially due to relatively high seasonal predictability over East Asia.

The East Asian climate is influenced by western tropical Pacific convection activity through atmospheric teleconnections. For instance, Nitta (1987) showed the Pacific-Japan (PJ) teleconnection pattern propagating from active convection over the subtropical western Pacific near 20°N. The regions of convection over the western tropical Pacific were positively correlated with geopotential height at 500hPa around Japan in boreal summer. The relationship in boreal winter between the geopotential height at 500 hPa around Japan and the western tropical Pacific convection is also pointed out e.g., in Ose, 2000. Therefore, predictability of convective activity over the western tropical Pacific is the key for seasonal prediction over East Asia.

Although the two-tiered seasonal forecast system can give us useful seasonal forecast skill in practice, the real air-sea interaction in the western tropical Pacific is not simple. This suggests that atmosphere-ocean coupled models or one-tiered seasonal forecast systems are necessary for predicting precipitation over the western tropical Pacific through physically correct model simulations (Kobayashi et al., 2005).

A new version of the ENSO and seasonal forecast system has been developed at JMA/MRI. Here we show the seasonal hindcast skill related to the western tropical Pacific precipitation and the Asian Monsoon in comparison with that of the operationally adapted two-tiered seasonal forecast system.

2. Why is HINDCAST (persistent SST) better than SMIP (real SST)?

Two sets of simulations have been carried out with the JMA operational AGCM (JMA, 2002). One is the set of integrations

From Palmer et al page 6: Seasonal Forecast Datasets - A Resource for Calibrating Regional Climate Change Projections?

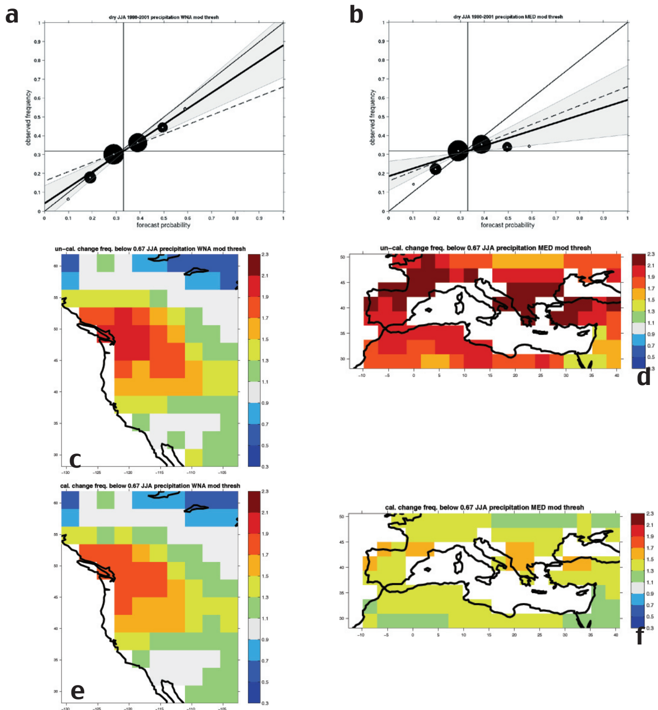


Figure 1: (Top row) Attribute diagrams for the DEMETER multi-model seasonal forecasts initialized on the 1st of May for Western North America (left) and the Mediterranean (right) regions. The diagrams have been calculated over the forecast period 1980-2001 for the event "summer anomalies below the lower tercile" using 1-month lead ensembles. The area of the solid circles is proportional to the bin population. The horizontal and vertical solid lines indicate the climatological frequency of the event in the observations and mean forecast probability, respectively. The dashed line separates skilful from unskilful regions in the diagram: points with forecast probabilities smaller (larger) than the climatological frequency that fall below (above) this line, contribute to positive Brier skill score (BSS); otherwise they contribute negatively to the BSS. Shaded areas indicate the uncertainty of the regression line estimation based on a 10,000 bootstrap re-sampling procedure. (Middle row) Ratio of the probability of dry summers (June-August) under ACC, estimated as the ratio of the probabilities of the AR4 multi-model multi-scenario ensemble near the end of the 21st Century (2081-2100) relative to the 1971-1990 reference probability (by definition, one third). (Bottom row) Same as the middle row, but for the calibrated ratio of probabilities.

From Coelho et al, page 13: Integrated seasonal climate forecasts for South America

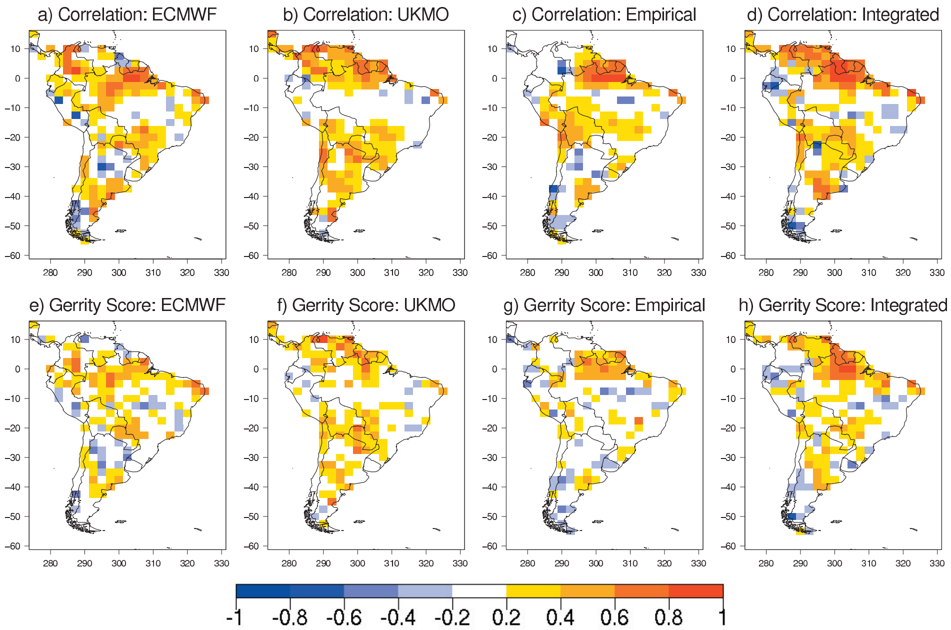


Figure 1: Correlation maps (panels a-d) and Gerrity score maps (panels e-h) of ECMWF, UKMO, empirical and integrated one month lead June-July-August precipitation forecasts for the period 1987–2001.

From Cavalcanti et al page 19: Austral summer precipitation over South America based on SMIP simulations

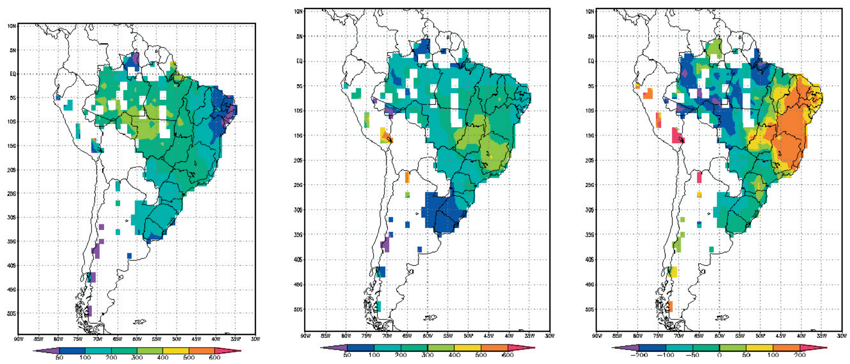


Fig.1 left: Mean DJF observed precipitation (mm); centre: Mean CPTEC/COLA AGCM precipitation; right: Difference AGCM-observation

From Cavalcanti et al page 15: Austral summer precipitation over South America based on SMIP simulations

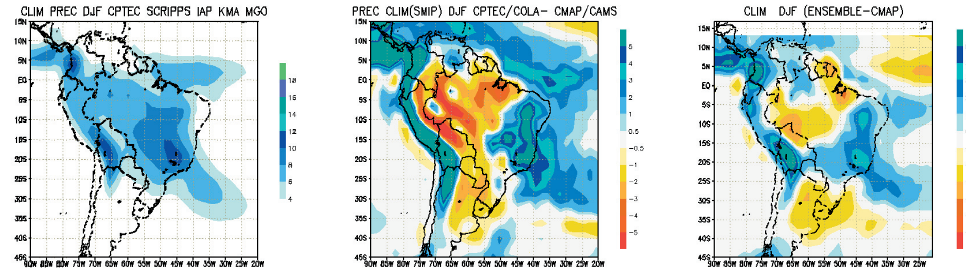


Figure 2. left: Mean DJF Multi-model ensemble precipitation (1979-2001) (mm/day); centre: (CPTEC/COLA – CMAP/CAMS); right: Multi-Model ensemble- CMAP/CAMS.

From Grimm et al. page 16: Do seasonal forecasts reproduce the link between early and peak monsoon rainfall in South America?

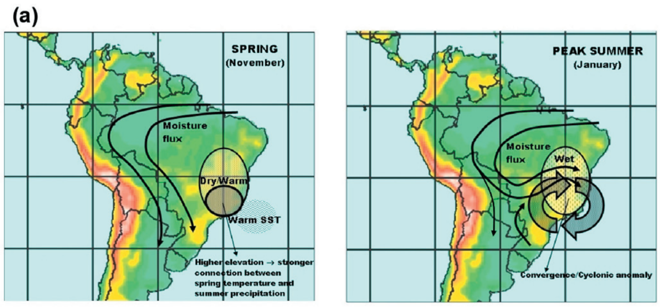
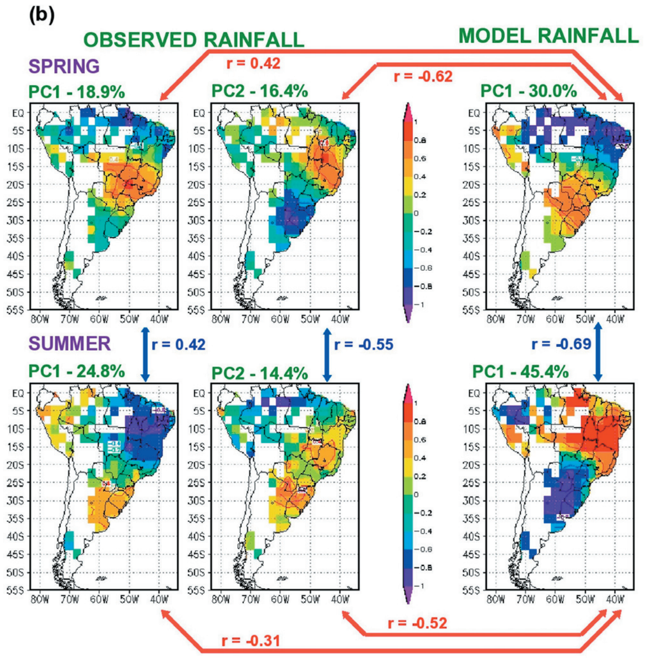


Fig. 1. (a) Schematic evolution from spring dry conditions to peak summer wet conditions in Central-East Brazil, through decreasing low-level pressure, convergence and cyclonic anomaly over Southeast Brazil (from Grimm et al. 2007). (b) First and second variability modes for observed spring and summer rainfall (left panels), and the first modes for the model simulated rainfall (right panels). The correlation coefficients between PCs of the observed and model modes are displayed in red, while the correlation coefficients between PCs for spring and summer are displayed in blue. All but one correlation coefficient are significant to levels better than 0.05 (for which r=0.37). Also shown are the fractions of variance explained by each mode.



From Wang et al, page 17: Coupled Predictability of the Seasonal Tropical Precipitation

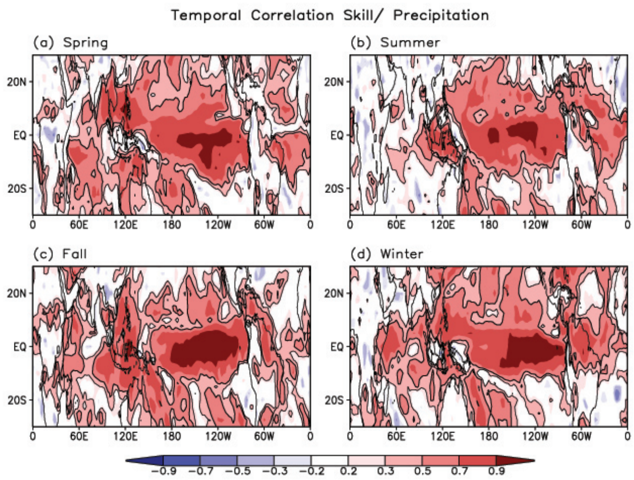


Figure 1: Spatial distribution of correlation coefficients between the predicted and the corresponding observed precipitation for the 21 years of 1981-2001 in (a) spring, (b) summer, (c) fall, and (d) winter using 10 coupled models which participate in APCC/CliPAS and DEMETER project

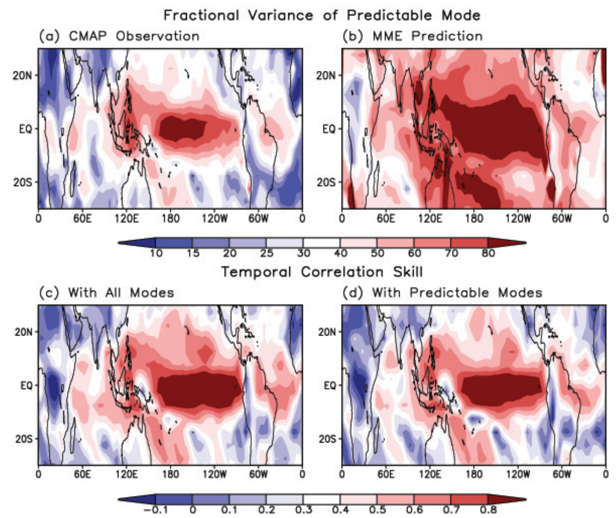


Figure 3: Fractional variance of predictable parts of S-EOF modes (upper panels) in observations and MME prediction. The temporal correlation coefficients between the observed and the predicted precipitation using all modes and predictable modes (lower panels). All seasons are used to obtain the results.

From Wang et al, page 17: Coupled Predictability of the Seasonal Tropical Precipitation

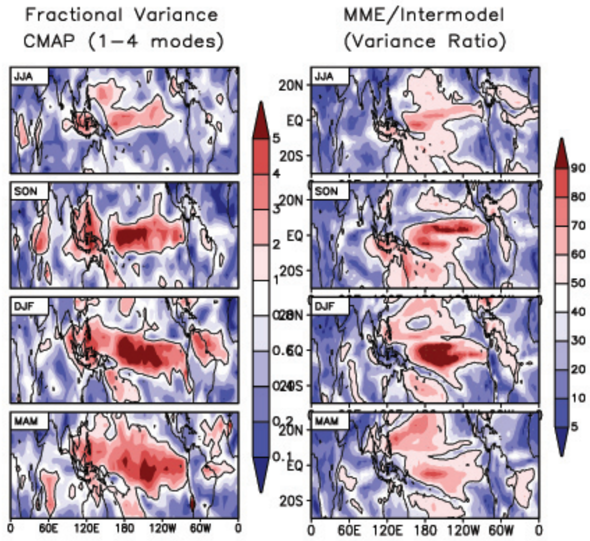


Figure 4: The ratio of interannual variance of fractional variance of predictable parts of S-EOF modes ((left panels) and MME to intermodel ensemble variance (right panels) for four seasons.

From Yasuda et al, page 18: Asian Monsoon Predictability in JMA/MRI Seasonal Forecast System

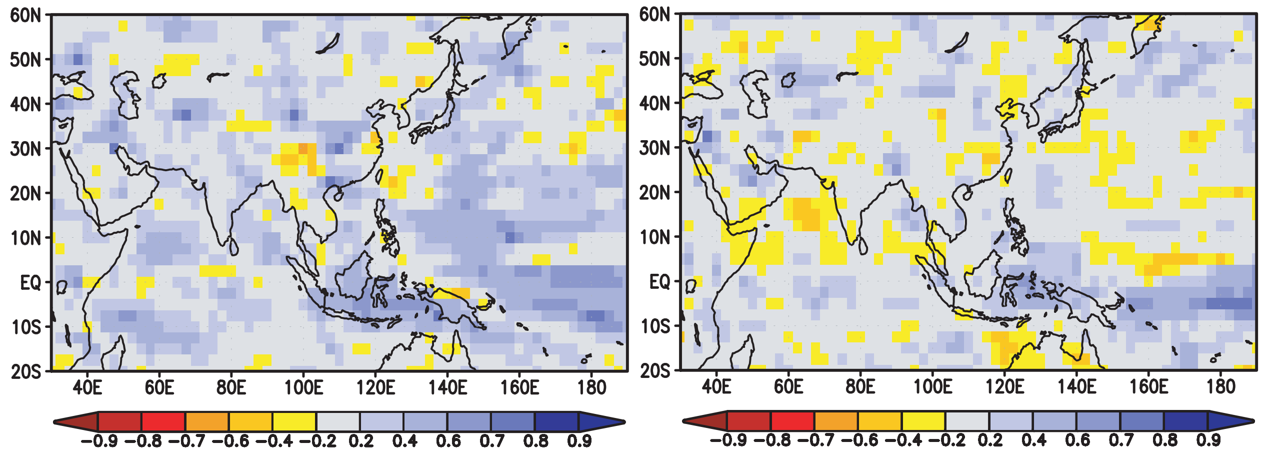


Figure.3 Anomaly correlation maps of rainfall in June-August during 1984-2005 at a lead time of 4 months in JMA/MRI-CGCM (left panel) and the 2-tiered operational AGCM (GSM0703C: right panel).

From Moron et al, Page 25: Seasonal Predictability of monsoon onset over the Philippines

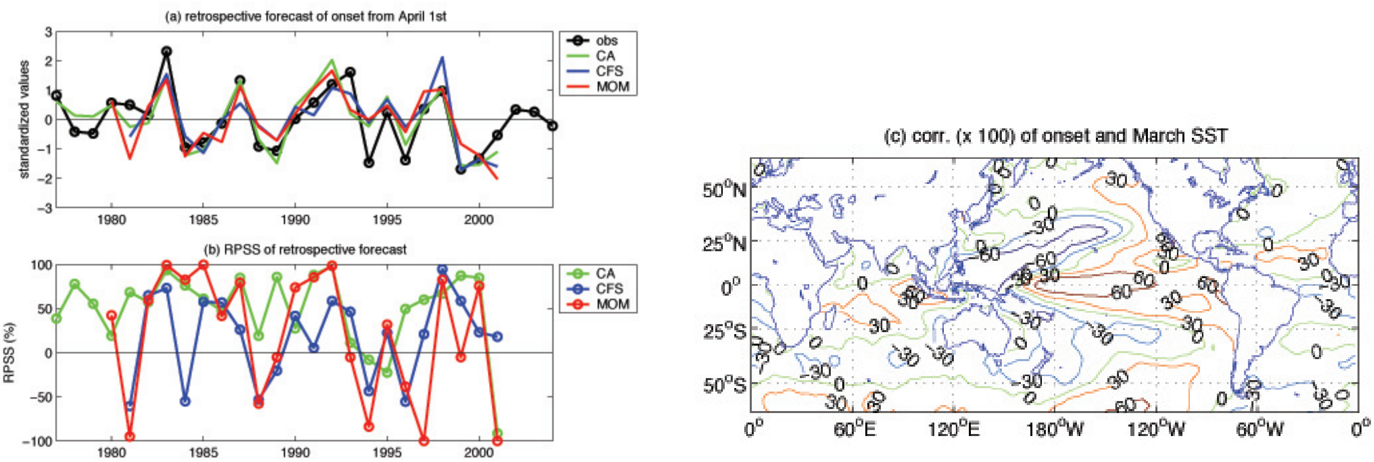


Figure 3 : (a) Downscaled retrospective GCM forecasts of the SAI of onset date. (b) The Ranked Probability Skill Score (RPSS). Key: station observation (black), ECHAM4.5-CA two-tier model (green), NCEP CFS (blue), and ECHAM4.5-MOM3 (red). The RPSS below – 100% are reset to –100%. (c) Correlations x 100 between the observed SAI of onset date and monthly sea surface temperatures in March. Contours are displayed at 30 intervals.

From Landman, Page 26, The influence of ENSO on operational rainfall forecast skill for South Africa

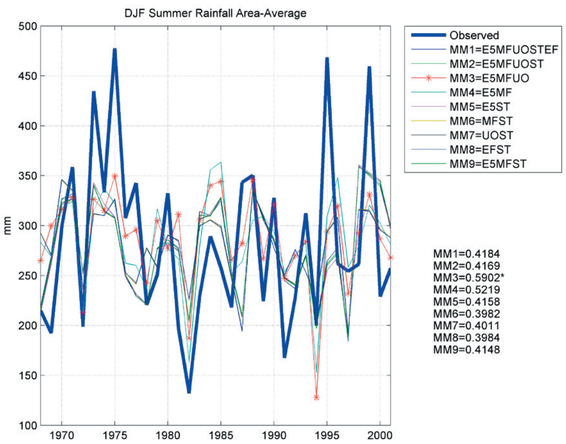


Figure 1. Observed versus multi-model forecast area-averaged values for DJF rainfall in mm over the 34-year test period. Nine multi-model systems are presented. The individual models considered in the various multi-models are ECHAM4.5 (E5), Météo-France (MF), UKMO (UO), SST-rainfall (ST) and ECMWF (EF). The best multi-model is indicated with an asterisk. The years on the x-axis refer to the December months of the DJF seasons.

From Hendon et al, Page 28: Seasonal Prediction of the Leeuwin Current

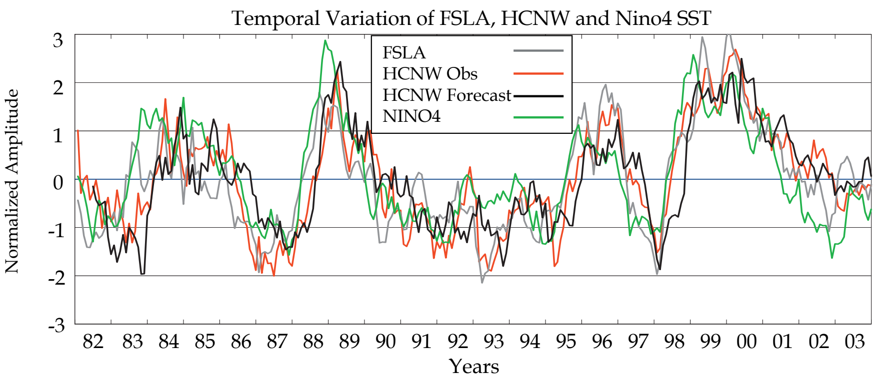


Fig. 1 Monthly time series of Fremantle sea level anomaly (FSLA), Nino4 SST index, observed HCNW (heat content averaged 15S-25S, 112E-120E), and predicted HCNW at 6 month lead time.

From Lavers et al, Page 33 Comparison of the potential skill of raw and downscaled GCM output for river flow forecasting: a UK case study

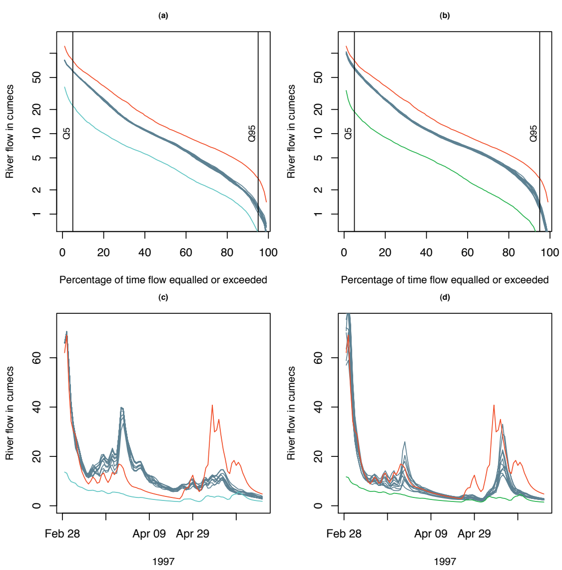


Figure 2: Flow duration curves for the River Dyfi at Dyfi Bridge for ERA-40 resolution 1.5 (a) and 2.5 (b) for 1991-2001, and the hydrographs for March 1997 - May 1997 are shown for ERA-40 resolution 1.5 (c) and 2.5 (d) (PDM modelled flow from observations (red); modelled flow from the ERA-40 resolution 1.5 (blue, (a) and (c)); modelled flow from ERA-40 resolution 2.5 (green, (b) and (d)), and modelled flow from the downscaled rainfall series (grey)).

From Jones et al, page 34: DEMETER-driven prediction of epidemic malaria in AFrica: Initial results from a continental-scale study.

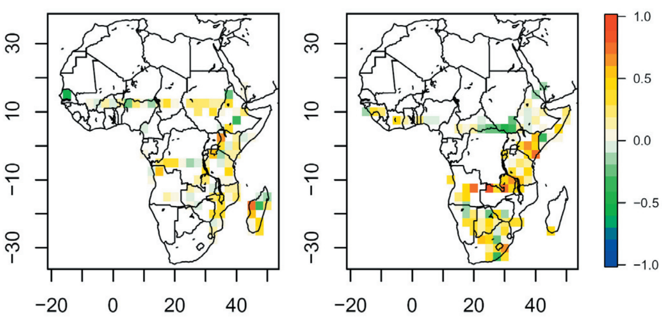


Figure 1 Tier-2 ROC skill scores (ROCSS, where a score above zero indicates skill relative to climatology) for above the median malaria event, DEMETER-driven LMM forecasts minus ROCSS for control run (where positive). Scores were calculated at tier-2 relative to ERA-40 driven LMM malaria incidence for the same period. May forecast months 4-6 (left) and November forecast months 4-6 (right). (Results masked to show only grid points with CoV>0.5 for ERA-40 driven LMM malaria incidence)

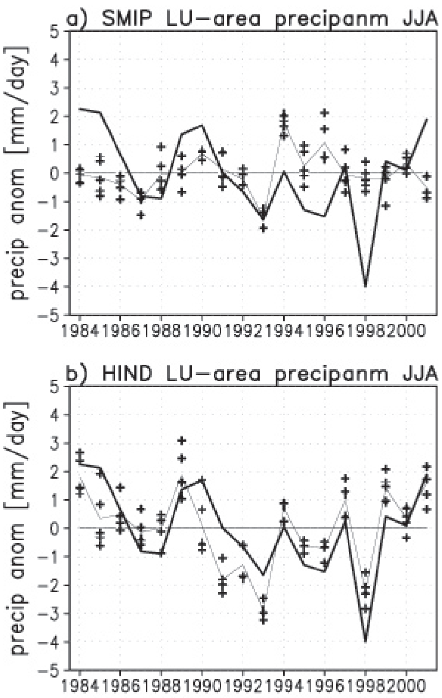


Figure 1: Interannual variations of precipitation anomalies over the subtropical western Pacific (110°E-160°E, 10°N-20°N) in JJA a) SMIP b) HINDCAST. Thick line indicates CMAP anomalies. Thin line indicates ensemble mean anomalies. Cross indicates precipitation anomalies of individual members. All anomalies are the deviation from 18-year (1984-2001) average.

with prescribed "observed" SSTs, called "SMIP". These "observed" SSTs and sea ice concentrations were prepared for SMIP2 simulations as boundary conditions. The other simulation is prescribed by "predicted" SSTs, called "HINDCAST". The "predicted" SSTs are assumed to be persistent from initial times during the forecast period as in the JMA operational system. Time integrations were approximately 3 months. Each simulation consists of 5 ensemble members.

The DJF mean precipitation predictability over the tropics in SMIP is higher than that in the HINDCAST, as expected (not shown here). Interestingly, the predictability of JJA mean precipitation over the western tropical Pacific in SMIP (real SST anomaly case) is lower than that in HINDCAST (persistent SST anomaly case). This is shown in the inter-annual variations of precipitation anomalies over the tropical western Pacific (110°E-160°E, 10°N-20°N) in JJA in Figure 1. The predictability in HINDCAST (r=0.75) is higher than that in SMIP(r=0.33).

The reason is associated with the lagged correlation between precipitation and local SST over the western tropical Pacific (110°E-160°E, 10°N-20°N) for the period from 1979 to 2001, as shown in Figure 2. The JJA mean precipitation is negatively correlated with JJA mean SSTs. The JJA mean precipitation has a weak positive lead correlation with SSTs in April-June (AMJ). The precipitation in early summer (May-July (MJJ)) has a positive correlation with SSTs in March-May (MAM).

Wang et al (2004) indicate that the rainfall anomalies are positively correlated with SST anomalies in nearly all models (11 models) that participated in the Asian-Australian monsoon Panel AGCM Intercomparison Project. It is confirmed that this is the case for the JMA operational AGCM (Kobayashi et al., 2005). Furthermore, it is pointed out that the CGCMs realistically reproduce the correct air-sea interaction and improve the forecast skill of the Asian summer monsoon (Kobayashi et al., 2005, Krishna Kumar et al. 2005).

Therefore, we suppose that the low (high) predictability of convective activities over the western tropical Pacific in SMIP (HINDCAST) is attributed to the combination of the lagged precipitation-SST relationship over the western tropical Pacific and the AGCM characteristics.

3. A new version of JMA coupled forecast system

A new atmosphere-ocean coupled model for the ENSO and seasonal prediction system (JMA/MRI-CGCM) has been developed at JMA/MRI. The atmosphere component is updated to a recent version of the JMA numerical forecast model. The resolution has been increased from T42L40 to TL95L40.

The ocean component is the MRI Community Ocean Model (MRI.COM) which is a z-coordinate ocean general circulation model developed at MRI. The horizontal resolution has been also increased from 2.5° in longitude and 0.5-2° in latitude to 1.0° in longitude and 0.3-1.0° in latitude, and the vertical resolution is increased from 20 to 50 levels (24 levels in the upper 200m).

The data assimilation system used to create initial conditions for ocean is the Multivariate Ocean Variational Estimation (MOVE) System developed at MRI (MOVE/MRI.COM; Usui et al. 2006). The analysis method of the MOVE System is a Three-Dimensional Variational (3DVAR) method with coupled temperature-salinity empirical orthogonal function (EOF) modes. The flux adjustments for heat and momentum in the new system are generally smaller than those in the current operational system.

We carried out the 5-member ensemble hindcast with the new forecast system (JMA/MRI-CGCM) initiated at the end of January, April, July and October from 1979 to 2006, as a part of the TFSP retrospective seasonal forecast experiment. It was found that the anomaly correlation of monthly mean SST for the Nino3.4 region is 0.75 at a lead time of 6 months, which is better than the results of the JMA operational ENSO forecast model. The new model also provides an important advance in predicting SST in the western tropical Pacific (0°-15°N, 130°E-150°E).

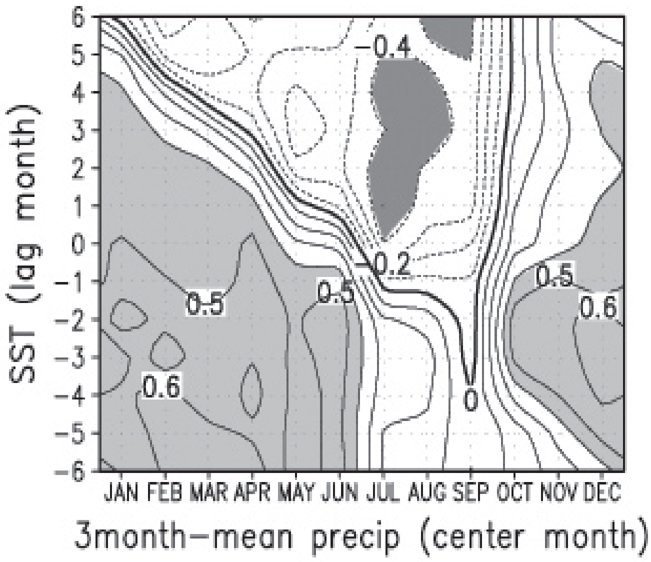


Figure 2: Lagged correlation between precipitation in CMAP and NCEP SST over the subtropical western Pacific (110°E-160°E, 10°N-20°N). Contour interval is 0.2. Dark shaded regions indicate a negative correlation coefficient area of less than -0.4. Light shaded regions indicate a positive correlation coefficient area of more than 0.4.

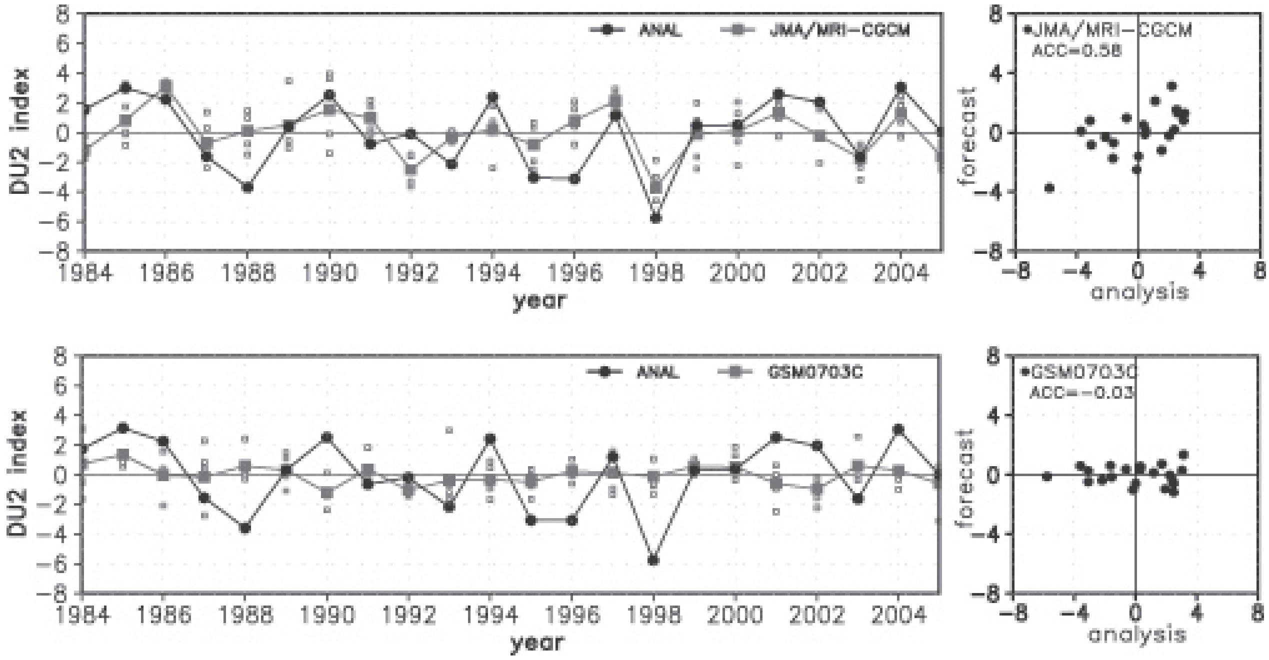


Figure.4 Time series of the DU2-index (right panel) and its scatter plots (left panel) from the 4-month-lead prediction by JMA/MRI-CGCM (top) and the JMA 2-tiered operational model (GSM0703C: bottom). The closed circles and closed squares show the indices calculated from reanalysis (JRA-25) and models, respectively. Open squares show the results of the individual members.

4. Asian Summer Monsoon Prediction

In recent years, it has been pointed out that prediction with coupled models improves the prediction skill in the Asian summer monsoon region (Krishna Kumar et al. 2005). Here we compare the 4-month-lead prediction results of the new system with those of the JMA 2-tiered operational seasonal prediction model (GSM0703C) based on the 5-member ensemble hindcast experiments.

Figure 3 (page 21) shows anomaly correlation maps between CMAP and 4-month-lead forecast rainfall for June-August. The progress in the JMA/MRI-CGCM is evident over almost all regions from the Indian Ocean to the western tropical Pacific.

The summer climate in Japan is influenced by the Southeast Asian Monsoon (SEAM) condition through the teleconnection pattern known as the PJ pattern (Nitta 1987). Interannual variability of the circulation index (DU2 index), which is closely related to the PJ pattern, defined by the difference of zonal wind anomaly at 850 hPa between the area (5°N-15°N, 90°E-130°E) and the area (22.5°N-32.5°N, 110°E-140°E) is shown in Figure 4. The JMA/MRI-CGCM significantly improves the 4-month-lead prediction skill of the SEAM variability compared with the JMA 2-tiered operational forecast model.

The south Asian monsoon represented by Webster-Yang index (W-Y index; Webster and Yang 1992) is also much improved with increased temporal correlation coefficients from 0.35 to 0.59.

5. Summary

The predictability of western tropical Pacific precipitation is the key for seasonal forecasts in East Asia. It is shown why the AGCM two-tiered system gives good one-month-lead JJA seasonal forecasts of the western tropical Pacific precipitation.

The realistic relationship between SST and rainfall is not reproduced in the AGCM but is in the CGCM through its physically correct air-sea interactions. The Asian summer monsoon is well predicted by the new forecast system (JMA/MRI-CGCM) at a lead time of 4 months in addition to much progress on the prediction skill of SST in ENSO. This version of the coupled forecast system will replace the current JMA operational ENSO forecast system in 2008. We continue to develop a next version of the seasonal forecast system to replace the JMA operational seasonal prediction system in a few years.

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Seasonal Predictability of monsoon onset over the Philippines

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1. Introduction

Tropical rainfall is often concentrated during a well-defined rainy season whose amplitude, length and onset vary by location. Interannual variability is known to be strongly influenced by the El Niño Southern Oscillation (ENSO) in many cases, but seasonal forecasts are still largely restricted to 3-month averaged rainfall amount at the GCM grid-point scale of about 300km (for example, http://iri.columbia.edu).

It is still not well established how this seasonally-averaged predictable signal is disaggregated at smaller spatial and temporal scales. We investigate here the seasonal predictability of the onset date of the rainy season across the Philippines. Onset date is particularly critical for agricultural activities and the estimate of its potential predictability is especially sensitive in the tropics where a significant part of the Gross National Product is often derived from a small number of crops. The mean onset of boreal summer monsoon in Southeast (SE) Asia and especially around the Philippines has been previously described as a sharp transition between two different states at large-scale (i.e. Akasaka et al., 2007), suggesting a potentially predictable component. We examine this issue using a well-sampled 77-station network over the Philippines provided by PAGASA (1977-2004), together with ensembles of retrospective forecasts from three seasonal prediction models (both one-tier and two-tier) initialized on April 1st.

2. Mean annual cycle and monsoon onset date

The Philippines combine a complex topography with islands of different sizes surrounded by warm sea surface temperatures (SSTs). The multi-scale mixing of processes is particularly challenging for the detection of any spatially-coherent regional-scale signal, for example related to ENSO (Lyon et al., 2006). We firstly examine the mean annual cycle of station rainfall and its spatial characteristics. Figure 1 shows the classification of mean annual cycle of rainfall at the 77 stations using a standard k-means classification on the mean probability of occurrence of wet days > 1 mm, low-pass filtered < 1/30 cycle-per-day. Use of the low-pass filtered mean daily rainfall amount leads to a similar pattern (not shown). The major spatial differentiation is between the eastern and western Philippines. The eastern part has no real dry season with two rainy peaks in November-December and late June-early July (Figure 1c), while the western part displays a sharp increase between a dry season till April and a wet season peaking around July-August (Figure 1b); we focus henceforth on the latter, defined by cluster 1.

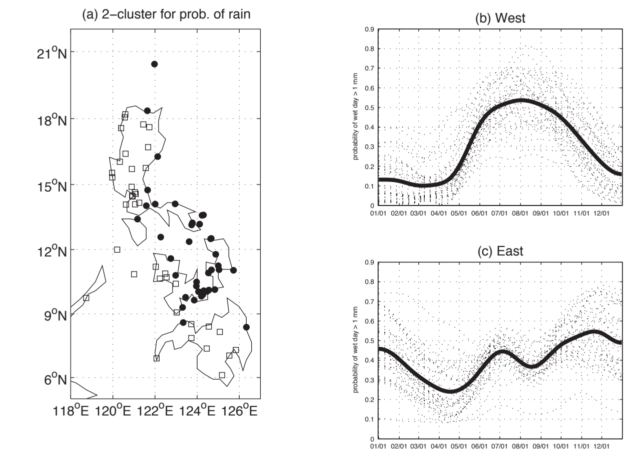

Figure 1 : Cluster analysis of the mean annual cycle of daily station rainfall (= daily average across the years of the frequency of occurrence of wet days > 1 mm low-pass filtered < 1/30 cycle-per-day) into two clusters using k-means. Panel (a) shows the resulting partition of the stations, with the mean seasonal evolution of rainfall at each station in the two sets of station plotted in panels (b) and (c). The bold line denotes the station average.

Rainy-season onset date is usually defined using thresholds for estimating the first wet spell of the season (i.e. Dodd and Jolliffe, 2001). Restriction to large rainfall amounts and/or long wet spells help to reduce the small-scale noise associated with the convective nature of tropical rainfall. The onset date is defined here as the first wet day of a 5-day sequence receiving at least 40 mm without any following dry spells of 15 consecutive days receiving less than 5 mm, within a month from the onset. Figure 2a shows the mean onset dates for the 38 western Philippines stations (i.e. white squares on Figure 1a); the onset combines a regional-scale signal centred around mid-May with local-scale variations, even between nearby stations. These local variations could be associated with topographic features that tend to enhance local rainfall intensities and thus slightly modify the phase of the rainy season. Figure 2b shows the standardized anomalies of the 38 stations together with the average, i.e. the standardized anomaly index (SAI ; Moron et al., 2007a). There are some deviations amongst the stations but the SAI exhibits a significant common signal (common variance amongst the stations = 25.4%), suggesting potential predictability at the station scale. Note that SAI is correlated > 0.97 with the leading EOF computed over the 38 stations, that accounts for 31.5% of the total variance.

3. Downscaled GCM hindcasts of the SAI of onset date

We next estimate seasonal hindcast skill of the SAI of onset date from three seasonal prediction models – the 24 runs of ECHAM4.5/constructed analog SST two-tier system of IRI (Li and Goddard, 2005), the 7 runs of ECHAM4.5-MOM3 coupled GCM (DeWitt, 2005), and the 15 runs of NCEP CFS model

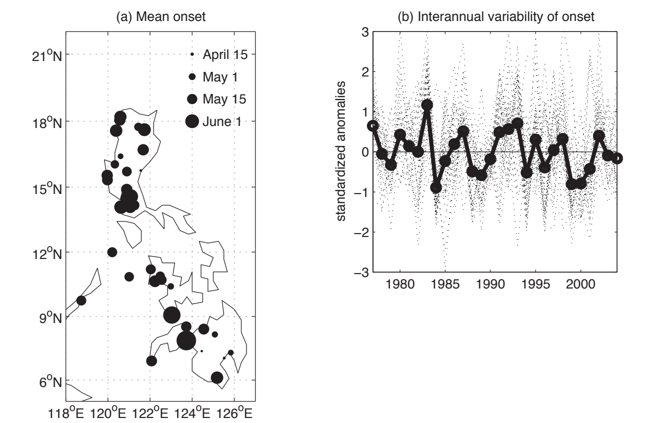

Figure 2 : (a) Mean onset date for stations in the western cluster in Fig 1a. (b) Standardized interannual time series of onset date for each station (dots) with the spatial average (i.e. the Standardized Anomaly Index, SAI) (bold line with circles).

(Saha et al., 2006), each initialized on April 1st. Downscaling to daily station rainfall is carried out stochastically using a 2-tier resampling scheme based on using gridded regional-scale seasonal-average and daily winds at 850 and 200 hPa as predictors in a k-nearest neighbour algorithm (Moron et al., 2007b). Basically, the seasons are first sampled based on the similarity between each GCM run and ERA-40 used as a library (but the year to be forecast is systematically excluded from the library) and then days are stochastically resampled in the seasons pooled from the first step. Each run is processed independently at this step and 5 daily sequences at local scale are extracted for each of them. The onset is then recomputed on resampled sequences and the standardized observed and simulated SAI is shown in Figure 3a (page 21) with the observed one.

The hindcast skill in terms of anomaly correlation coefficient between observed and ensemble-mean hindcast SAIs equals 0.84 (ECHAM-CA), 0.78 (CFS) and 0.70 (ECHAM-MOM). Fig. 3b shows the ranked probability skills score (RPSS) for tercile categories using the whole distribution of 120 (ECHAM-CA), 75 (CFS) and 35 (ECHAM-MOM) simulations of SAI. Median RPSS equals respectively 60% (ECHAM-CA), 23% (CFS) and 42% (ECHAM-MOM).

4. Conclusion

Our results demonstrate substantial predictability in rainy season (monsoon) onset date over the western Philippines that is robust across retrospective forecasts made with three current seasonal prediction GCM systems, based on an agronomic definition of onset, averaged over 38 stations. If the more localized definition of onset used by PAGASA is used, based on 8 stations, then the ACC scores decrease to 0.50-0.55. This decrease is likely to be a function of the station-scale noise component evident in Fig. 2a, and highlights the importance of defining onset from some optimal combination of predictability and end-user perspectives, depending on the specific application.

Regarding the source of predictability, Fig. 3c shows the correlations between the SAI onset date and March SST (i.e., the month prior to initialization of the forecasts). The pattern exhibits strong correlations over the Tropical central and eastern Pacific typical of ENSO. However, the correlations are also very high (up to –0.8) over the northwestern Tropical Pacific, suggesting the role of regional processes as well. Further work is required to explore potential improvements through multi-model ensemble of GCMs and empirical models, to determine the most appropriate definitions of onset for applications in the Philippines, and to investigate any additional predictability of onset associated with intraseasonal oscillations.

Acknowledgments

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The influence of ENSO on operational rainfall forecast skill for South Africa

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Introduction

The South African Weather Service (SAWS: http://www.weathersa.co.za) issues forecasts of rainfall and temperature at various time ranges, including forecasts on seasonal time scales. For this purpose, seasonal forecast maps and output data from a number of general circulation models (GCMs) are obtained from international centres (e.g., the International Research Institute for Climate and Society – IRI) and then subjectively combined with forecasts produced by the seasonal forecasting systems developed at the SAWS. These systems include rainfall-sea-surface temperature (SST) empirical models (Landman and Mason, 1999) and ECHAM4.5 (Roeckner et al., 1996) forecasts that are additionally downscaled statistically to 963 rainfall stations evenly distributed across South Africa (Landman and Goddard, 2005). The SAWS is currently developing an objective forecasting system that is based on a multi-model forecasting approach. Such a system will replace the current subjective forecasting system that relies heavily on forecasters' interpretation of model output. In addition to removing the subjectivity of the current forecasting system, there are advantages in combining a number of GCMs into a multi-model ensemble since GCMs differ in their parameterizations and therefore differ in their performance under different conditions (Krishnamurti et al., 2000). Multi-model systems are nearly always better than any of the individual systems (Doblas-Reyes et al., 2000, Krishnamurti et al., 2000), but the multi-model approach is only beneficial if the individual systems produce independent skilful information (Graham et al. 2000).

An association exists between South Africa's summer seasonal rainfall and the equatorial Pacific Ocean. However, this link is not always strong since the association in the middle to late austral summer season is higher than earlier in the summer rainy season (e.g., Tyson and Preston-Whyte, 2000). Notwithstanding, in the mid-summer months South Africa tends to be anomalously dry during El Niño years and anomalously wet during La Niña years. Indian and Atlantic Ocean SST also have a statistically detectable influence on South African rainfall variability (e.g., Mason, 1995; Reason et al., 2006). Moreover, while the El Niño-Southern Oscillation (ENSO) has a control on rainfall variability over the southern African region, Indian Ocean SST anomalies, sometimes varying independently of ENSO, are important for atmospheric GCMs to simulate skilfully southern African seasonal rainfall (e.g., Washington and Preston, 2006). This paper aims to show the extent to which ENSO influences operational South African summer rainfall forecast skill of a state-of-the-art multi-model forecasting system.

Data and method

The December-January-February (DJF) seasonal total rainfall for 963 SAWS stations evenly distributed over South Africa is the set of predictands in a model output statistics (MOS; Wilks, 2006) approach that uses a combination of large-scale total rainfall fields from a range of physical models as the set of predictors. The model fields used in the MOS are restricted over a domain that covers an area between 10°S and 40°S, Greenwich to 60°E. The physical forecast models' output used here are from three coupled models from the DEMETER project (Palmer et al., 2004) (UKMO, ECMWF and Météo-France) and from one atmospheric model, the ECHAM4.5, obtained from the IRI. A canonical correlation analysis (CCA) model that uses near-global SSTs as predictor is considered as a fifth model in designing a multi-model seasonal rainfall forecasting system for South Africa. A one-month lead-time is imposed for each of the four models, i.e., forecasts made in November for a DJF rainfall forecast.

MOS is subsequently applied to the total rainfall forecast fields of each of the four physical models. Using MOS to recalibrate GCM output produces improved forecast skill over southern Africa (Landman and Goddard, 2002). The individual performances of the MOS models and the rainfall-SST statistical model are tested using a 5-year-out cross-validation design over the 34-year period from 1968/69 to 2001/02. The most skilful of the five models is considered to be the one with the highest area-averaged cross-validation correlation value and the least skilful the one with the lowest value. Area-averages are calculated using only those stations that get most of their rainfall during the austral summer (758 stations). The correlation values are adjusted using the Fischer Z transformation (Wilks, 2006).

A number of forecast combining algorithms exists. In this paper CCA is used for model combination. The Climate Predictability Tool (CPT) software developed at the IRI is used for this purpose. First, all the models' output is combined in one predictor field for a five-model multi-model system. A multi-model system of four models is considered next by discarding the model with the lowest skill. This backward elimination of the models is performed by each time discarding the model with the lowest skill until only two models are considered in a multi-model system. In addition to these multi-model systems, each physical model's forecasts are also individually combined with the forecasts of the rainfall-SST statistical model. Finally, the best two physical models are also combined with the rainfall-SST statistical model. Nine multi-model systems are subsequently considered. The performance of the multi-model systems is also tested using a 5-year-our cross-validation design over the 34-year test period.

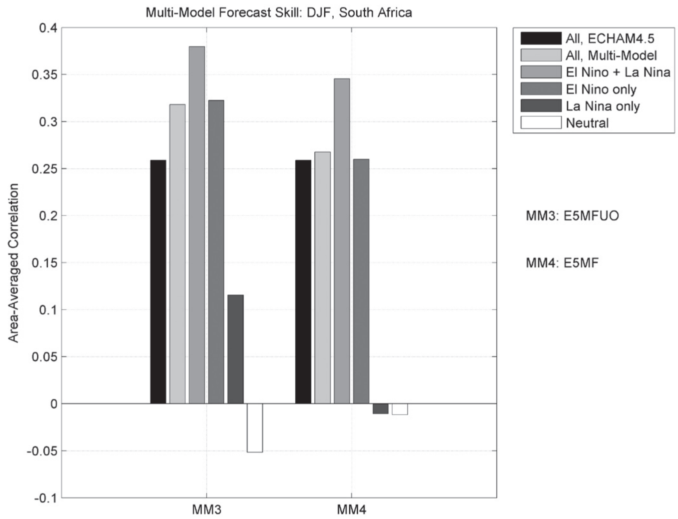

Figure 2. Area-averaged cross-validation correlations of the best single- and best two multi-model systems, considering all of the 34 years, El Niño together with La Niña years, only El Niño years, only La Niña years, and only neutral years.

Results

The ECHAM4.5-MOS model is found to perform the best over the 34-year test period. In descending order of skill, the next four models are the Météo-France-MOS model, the UKMO-MOS model, the rainfall-SST model and the ECMWF-MOS model. Figure 1 (page 22) shows the various multi-model cross-validated forecasts and the observed values in mm, both averaged over the summer rainfall stations. The correlation values between the area-averaged multi-model forecasts and the observed are also shown on the bottom right-hand side of the figure. MM3 (ECHAM4.5+Météo-France+UKMO) is associated with the highest correlation value (0.5902), followed by MM4 (ECHAM4.5+ Météo-France). Calculating the area-averaged adjusted correlation values produces the same results, i.e., MM3 is the most skilful system. Figure 1 shows that the intensity of the El Niño related observed drought years of 1972/73, 1982/83 and 1994/95 are well captured by the multi-model forecasts, while the extremely wet conditions observed during the La Niña seasons of 1973/74, 1975/76, 1995/96 and 1999/2000 are not captured by the forecasts (El Niño and La Niña years as defined by the Climate Prediction Centre). Figure 2 shows the area-averaged adjusted correlation values of the best single model and the best two multi-model systems. For each multi-model system, the area-averaged correlations are separately recalculated for El Niño, La Niña, El Niño together with La Niña years, and neutral years. Skill levels associated with El Niño together with La Niña years are much higher than during only La Niña years and also neutral years. In fact, negative correlation values are found for both multi-model systems when only neutral years are considered.

Discussion

Multi-model forecasting systems have the potential to outscore seasonal rainfall forecasts over South Africa produced by individual models. However, multi- and single model verification results for the austral spring months of September-October-November (SON) and the autumn months of March-April-May (MAM) show no improvement of the multi-model systems over the single model forecasts (not presented here). Mid-summer is the season of highest rainfall predictability and the DJF skill levels presented here are found to be a function of the state of the equatorial Pacific Ocean, and in particular whether or not an El Niño event is occurring. Limited skill in predicting DJF rainfall is found during La Niña years and even lower skill during years associated with neutral conditions in the equatorial Pacific Ocean. Notwithstanding, seasonal rainfall forecasts during El Niño together with La Niña years are the most skilful. Take note that the model skill levels presented are only for deterministic forecasts based on the ensemble mean of the various individual models. However, when considering the full ensemble (9 members) of each of the DEMETER physical models used here, the models are very confident (most of the ensemble members) in predicting drought conditions over South African during the DJF season of El Niño years, and also with some confidence in predicting wet conditions during La Niña years. Therefore, since the multi-models produce the best results during El Niño and La Niña years (particularly during El Niño years), and that they are very (fairly) confident in their forecasts of drought (wet conditions) during El Niño (La Niña) years, this suggests that the state-of-the-art forecasting systems considered here are to a large extent dictated by the models' response to the equatorial Pacific Ocean.

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Seasonal Prediction of the Leeuwin Current

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Introduction

Dynamical seasonal prediction using coupled atmosphere-ocean general circulation models (AOGCMs) is routinely performed at numerous national and international forecast and research centres. The foundation for predictions with such systems is the proven ability to predict the state of El Niño/Southern Oscillation (ENSO) at lead times up to about 12 months. Regional predictive skill outside of the tropical Pacific is primarily associated with teleconnections to ENSO, which the coupled AOGCMs presumably faithfully simulate. Most of the focus for application of dynamical seasonal prediction has been on exploiting the ability to predict the atmospheric teleconnections associated with ENSO, for obvious reasons. This note addresses the potential for dynamical seasonal prediction of variations of the poleward flowing Leeuwin Current, which is perhaps the most predictable component of the atmosphere-ocean climate system outside of the tropical Pacific (due to its extremely tight coupling to ENSO) and which also is of enormous economic and ecologic importance.

Leeuwin Current

Unlike the prominent equatorward flowing eastern boundary currents along the western coasts of the Americas and Africa, the Leeuwin Current flows poleward against the prevailing winds, transporting warm and fresh water south along the subtropical west coast of Australia. As a result, sea surface temperatures (SSTs) and mean rainfall are higher than at similar subtropical latitudes off the west coasts of the Americas and Africa (e.g., Feng et al. 2003). The transport of relatively fresh tropical water south along the coast also results in the appearance of many aquatic species (plants and fish) at higher latitudes than would otherwise be the case. Interannual variations of the current have profound and predictable impacts on a number of important fisheries (e.g., Pearce and Phillips 1988).

The Leeuwin Current is narrow (typical width <100 km) and displays pronounced mesoscale meanders and eddies (e.g., Legeckis and Cresswell 1981). The current is confined above about 300 m and is strongest at the surface. It exhibits a pronounced annual variation in strength, with peak volume transport ~ 5 Sv and peak velocity ~0.5 ms^{-1} occurring in winter when the equatorward component of the mean wind is weakest (Smith et al. 1991). The Leeuwin Current essentially exists because of the trade winds in the Pacific: warm, low density tropical Pacific water "leaks" into the Indian Ocean via the Indonesian Throughflow. As a result, a south-north pressure gradient in the south eastern Indian Ocean is maintained. This south-north pressure gradient drives an eastward, onshore geostrophic transport that overcomes the locally-driven offshore Ekman transport and downwells on the

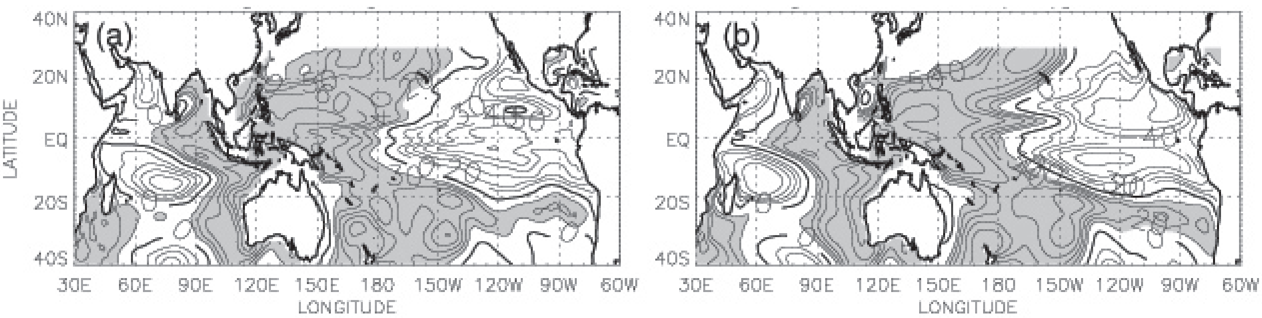

Fig. 2 Correlation of a) the monthly time series of FSLA with observed heat content from the POAMA assimilation and b) the monthly time series of observed HCNW with ensemble mean predicted heat content at 6 month lead time for period 1982-2003. Correlation is presented in percentage and drawn from ±20% with interval 10%. Zero contour is thick line

coast. The Leeuwin Current is in geostrophic balance with the resulting near-shore west-east pressure gradient (e.g., Godfrey and Ridgway 1985). Variations of the current on annual to interannual time scales are coastally trapped, with variations of current strength being well captured by a linear relationship with sea level deviation on the inshore side of the current at Fremantle (Feng et al. 2003).

The interannual variation of the current is dominated by ENSO (weak in El Niño years and strong in La Niña years; e.g., Pearce and Phillips 1988; Feng et al. 2003). This relationship is demonstrated in Figure 1 (page 22), which shows the monthly time series of the Niño4 SST index together with the observed sea level anomaly (smoothed with a running 3-month mean) at Fremantle (FSLA; which we take as an index of the strength of the Leeuwin Current following Feng et al. 2003). The correlation between them is ~0.75 at zero lag. This tight coupling with ENSO stems from the transmission of the sea level anomaly in the western Pacific (high during La Niña and low during El Niño) through the throughflow and southward along the Australian coast as a coastally trapped wave (e.g., Clarke and Liu 1994).

This mechanism of variability stemming from ENSO is demonstrated in Figure 2a, which shows the simultaneous correlation of FSLA with upper ocean heat content anomaly (defined here as the temperature averaged in the upper 300 m; which we use as representative of the large-scale geopotential or steric height anomaly) from the Australian Bureau of Meteorology POAMA (Predictive Ocean Atmosphere Model for Australia) ocean assimilation. High FSLA is associated with an east-west dipole anomaly of heat content across the Pacific that is reminiscent of the mature phase of La Niña. Positive anomalies on either side of the Equator in the west Pacific are indicative of the westward propagating Rossby waves that have encountered the western boundary and which appear to be transmitted through the Indonesian throughflow and southward onto the Australian coast. The heat content anomalies in the tropical Indian Ocean away from the coast in Figure 2a are interpreted as additional remote effects of ENSO (stemming both from atmospheric and oceanic teleconnections; e.g., Wiffels and Meyers 2003), rather than as a cause of variations of sea level at Fremantle.

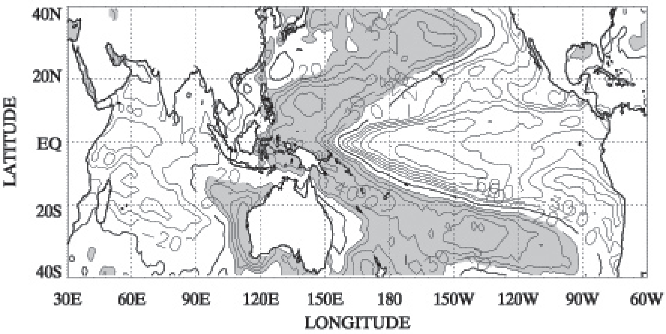

Fig. 3 Correlation of the monthly time series of FSLA with Reynolds OIv2 SST (obtained from http://www.cdc.noaa.gov/cdc/data.noaa.oisst.v2.html) for period 1982-2003. Colour scale is the same as in Fig. 2.

The impact of interannual variations of the Leeuwin Current on local SST along the west coast of Australia is demonstrated by the correlation of FSLA with SST (Figure 3). The region of strong positive SST correlation along the subtropical west coast of Australia nicely delineates the geographic domain and regional impact of the Leeuwin Current: An anomalously strong current, which originates ~30^o longitude off shore of the North West Cape and intensifies and contracts onto the coast to the south, is associated with anomalous poleward advection of the mean south-to-north SST gradient . The tight coupling of FSLA with ENSO is also reflected by the La Niña-pattern of SST correlation in the Pacific.

Dynamic Seasonal Prediction

The ability to predict seasonal variations of the strength of the Leeuwin Current is tantamount to the ability to predict the heat content anomalies on the northwest shelf of Australia that evolve during ENSO. Ideally, ocean (and atmosphere) models would have sufficient resolution and physics to allow direct prediction of the current variations to the south but the modest resolution of the models used for seasonal prediction is far below that required to resolve the detailed dynamics that govern the Leeuwin Current (e.g., Reason et al. 1999). Hence, we focus on prediction of the large scale heat content anomaly on the northwest shelf that is the primary driver of the current's variations. The utility of using heat content averaged on the northwest shelf (15^{o}S-25^{o}S, 112^{o}E-120^{o}E; hereafter HCNW) as a proxy for Leeuwin Current variations is demonstrated in Figure 1. The correlation of HCNW with FLSA exceeds 0.8.

The skill of predicting HCNW is assessed using the POAMA seasonal forecast system (http://poama.bom.gov.au). POAMA consists of a moderate resolution AGCM (T47/L17) coupled to the ACOM2 ocean model (2^o x 0.5^o resolution), which is a derivative of MOM-2. When run as a climate model, POAMA faithfully captures the evolution of heat content associated with ENSO, including the transmission through the Indonesian throughflow and onto the west Australian coast (Zhong et al. 2005). The analysis here is based on a 10 member hindcast set of 9 month forecasts that are initialized on the first of each month for the period 1982-2003. Ocean initial conditions on the first of each month are derived from the POAMA ocean assimilation system and atmospheric/land initial conditions are derived from ALI (Atmosphere-Land Initialization), which nudges the atmosphere-land models to the ERA-40 reanalysis. Perturbed atmospheric initial conditions are obtained by taking the nudged analysis from earlier and later 3 hour periods around the first of each month.

The POAMA system exhibits high skill (anomaly correlation exceeding 0.7) for predicting heat content anomaly throughout the equatorial central and east Pacific at lead times beyond 6 months (not shown), which is reflective of the ability of the POAMA system to predict ENSO. High skill is also evident off of the equator in the far west Pacific (presumably associated with the slow westward propagating Rossby waves generated during ENSO) and on the northwest shelf of Australia. This high skill on the northwest shelf reflects the ability to predict the oceanic teleconnection of ENSO from the Pacific, through the Indonesian throughflow. This is demonstrated in Figure 2b, which shows the correlation of the observed HCNW with the predicted heat content over the tropical Pacific and Indian Oceans at a 6 month lead time. The resemblance with the observed heat content anomaly that is associated with Fremantle sea level variation (Figure 2a) is outstanding.

Skill of predicting HCNW and the Niño4 SST index is summarized in Figure 4. Except at short lead time, the skill is essentially identical for both Niño4 and HCNW. The anomaly correlation for both remains high (>0.75) to 9 month lead time and readily beats persistence. In light of the tight coupling between HCNW and FLSA, skilful seasonal prediction of the Leeuwin Current appears to be as feasible as prediction of ENSO.

Concluding Remarks

This study is part of an ongoing investigation into seasonal predictability of the marine environment of Western Australia. Future work will include downscaling of the dynamical model predictions of heat content to direct prediction of Leeuwin Current strength, evaluation of the value added by prediction of heat content on the northwest shelf over that of simply predicting ENSO in the Pacific, and investigation of the role of coupled processes in the Indian Ocean for contributing to variability and predictability of the Leeuwin Current.

Acknowledgement

Ming Feng kindly provided his time series of Fremantle sea level anomaly. Support for this work was provided in part from the Western Australian Marine Science Institution (WAMSI) www.wamsi.org.au .

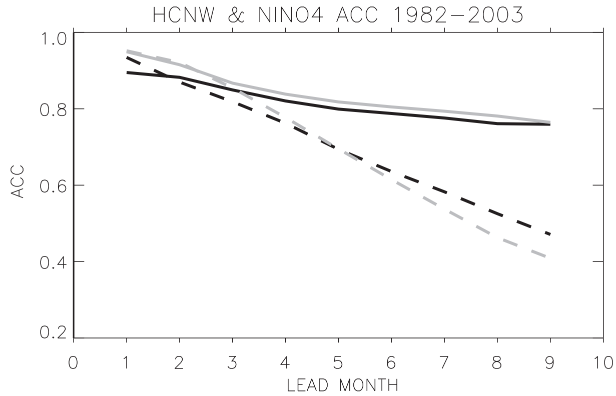

Fig. 4 Anomaly correlation for Nino4 SST index (grey) and HCNW (black) as a function of forecast lead time. Persistence (in dashed lines) is shown for reference. Correlation is computed using ensemble mean of forecasts for the period 1982-2003.

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Seasonal Rainfall Anomalies over Western Australia Forced by Indian Ocean SST – Scope for Improved Forecasting

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Introduction

On seasonal to interannual timescales, it is generally assumed that the ocean's role in modulating mid-latitude precipitation is minor relative to internal atmospheric variability. This is in contrast to the well-established view that air-sea coupling is of paramount importance in the tropics. In this study, we use atmospheric general circulation model (AGCM) simulations to assess the way in which Indian Ocean SST anomalies modulate mid-latitude precipitation across western regions of Australia. Our study represents an extension of previous work by England et al. (2006) who find that, in the observed record, extremes in southwest Western Australia (SWWA) rainfall are associated with characteristic SST patterns and changes in the large-scale atmospheric circulation across the Indian Ocean. Here, we show that these SST composite patterns can significantly affect SWWA and Western Australia precipitation in ensemble sets of AGCM simulations. We also propose a mechanism for the observed rainfall shifts due to changes in the large-scale general circulation (Ummenhofer et al., 2007).

Model and experimental setup

A set of ensemble experiments is conducted with the NCAR Community System Model, version 3 (CCSM3; Collins et al., 2006), run in uncoupled atmosphere-only mode. The atmospheric component of CCSM3, the Community Atmosphere Model (CAM3; Hurrell et al., 2006) uses a spectral dynamical core, T42 horizontal resolution (~2.8° latitude/longitude), and 26 vertical levels. Ummenhofer et al. (2007) assess the model's performance over the Indian Ocean and Australian region on seasonal to interannual timescales and demonstrate the model's suitability for the present study.

An 80-year integration forced by a 12-month SST climatology (Hurrell et al., 2006) represents the control experiment (CNTRL). Two sets of perturbation experiments are carried out where anomalous SST patterns are superimposed onto the climatology. These perturbations are derived from composites of observed average monthly SST anomalies for years defined as being anomalously dry/wet over SWWA (30°-35°S, 115°-120°E) by England et al. (2006), i.e. exceeding ±1 standard deviation in their rainfall time-series. The resulting monthly-varying SST anomalies are scaled by a factor of three in an attempt to excite a clearer atmospheric response from the inherently noisy atmosphere. Despite this scaling the applied magnitude of SST perturbations is not unrealistic, with certain years showing similar SST anomaly magnitudes (for further details see Ummenhofer et al., 2007). All of the "dry-year" (PDRY) and "wet-year" (PWET) perturbation runs start from early January from a variety of years spanning the control run. The ensemble sets consist of 60 one-year integrations for each of the PDRY and PWET scenarios.

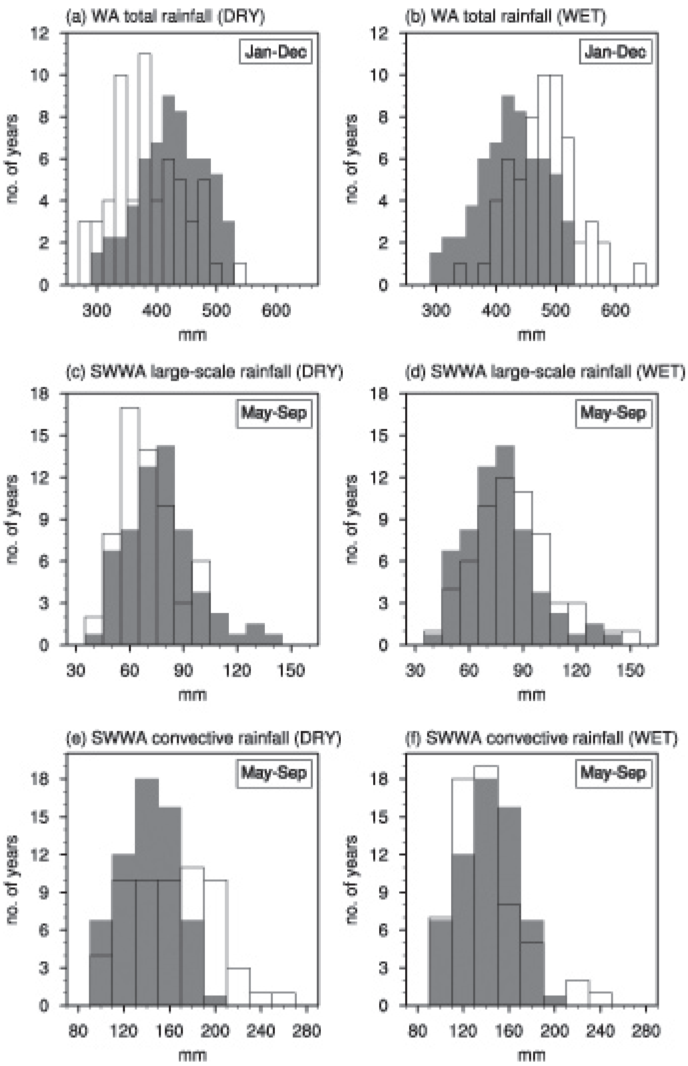

Figure 1. Frequency distribution of (a, b) total rainfall spatially averaged across WA; (c, d) large-scale and (e, f) convective rainfall spatially averaged across SWWA; cumulative rainfall amount (in mm) summed over the months indicated for PDRY (left) and PWET (right) cases. The shaded gray rainfall distribution represents the CNTRL (normalized to the number of ensemble members in PDRY/PWET), while PDRY and PWET are indicated with black outlines. The following significance levels hold, as determined by a Mann-Whitney test: (a) 99%, (b) 99%, (c) 99%, (d) 95%, (e) 99%. (adapted from Ummenhofer et al., 2007).

Rainfall shifts

The impact of the modified SST is assessed for precipitation across western regions of Australia. Fig. 1 shows the rainfall frequency distribution across the ensemble members in PDRY and PWET relative to the CNTRL. The total annual precipitation is spatially averaged over the region of Western Australia (WA; 21°-35°S, 115°-130°E). This area excludes the tropical north of the state dominated by monsoonal rainfall and integrates across coastal regions with predominant winter rainfall and dry regions farther inland with a more uniform annual rainfall distribution. The model results indicate a shift in the distribution towards lower (higher) rainfall amounts in the PDRY (PWET) case relative to the CNTRL (Fig. 1a, b; significant at the 99% confidence level).

The model distinguishes between large-scale and convective components of precipitation, providing a first insight into the likely causes for the simulated rainfall shifts. Over WA, these components reinforce each other and are of opposite sign for PDRY and PWET (Fig. 1a, b). This contrasts with the rainfall breakdown for the smaller area of SWWA (30°-35°S, 115°-120°E), where the two components are not necessarily of the same sign. As a result, large-scale and convective components are presented separately over the predominant SWWA rainfall season May-September (Fig. 1c-f). The large-scale rainfall distribution is shifted towards low (high) rainfall amounts for PDRY (PWET) relative to the CNTRL (Fig. 1c, d). A disproportionate decrease (increase) in the number of ensemble members receiving in excess of 100 mm (summed for May-September) is observed for PDRY (PWET). Only 5% of winters (May-September) in the PDRY case receive >100 mm, while this occurs in 13% of winters in the CNTRL and 22% in the PWET case. The frequency distribution for convective precipitation over SWWA shows less consistent shifts (Fig. 1e, f). Significantly more ensemble members receive high convective precipitation for PDRY relative to the CNTRL, while no significant change is recorded for PWET.

Atmospheric dynamics

To understand the mechanisms responsible for the observed shifts in precipitation, we investigate changes in the atmospheric general circulation induced by the SST perturbations. We focus on the May-September period, as most of the SWWA rain falls during these months (~70% of annual total) and the anomalies of various atmospheric variables are particularly strong during the winter season (Ummenhofer et al., 2007).

The SST anomalies during dry/wet years form a characteristic dipole pattern which is distinct in location and temporal evolution from previous definitions of dipoles in the Indian Ocean (e.g., Saji et al., 1999; Behera and Yamagata, 2001). A pole of cold (warm) SST anomalies develops in the eastern Indian Ocean over the northwest shelf of Australia (named P1) at the same time as warm (cold) anomalies form in the central subtropical Indian Ocean (named P2) for PDRY (PWET), reaching maximum magnitudes in late winter/early spring (Fig. 2a, b). Atmospheric thickness anomalies (1000-500 hPa) of the same sign and position as the underlying SST anomalies at P1 and P2 develop in the perturbation experiments, intensifying towards late winter and extending across southern regions of Australia (Fig. 2c, d). This leads to a weakening (intensification) of the meridional thickness gradient and the subtropical jet during the winter in PDRY (PWET), with a coincident easterly (westerly) anomaly in the thermal wind over southern regions of Australia. The offshore (onshore) wind anomalies over SWWA (Fig. 2e, f) thus contribute to the reduction (increase) in large-scale rainfall. In observations, Ansell et al. (2000) similarly associate variations (and trends) in SWWA rainfall with modulations in the subtropical high pressure belt and a shift of the circumpolar trough. However in their study, links with Indian and Pacific Ocean SST are weak compared to the variability of the large-scale atmospheric circulation, while we demonstrate that the reorganization in the general atmospheric circulation can arise as a result of the changed SST fields over the Indian Ocean.

A measure of the baroclinic stability in the atmosphere, and hence its disposition towards developing rain-bearing low pressure systems, is provided by the Eady growth rate. A reduction (increase) in the Eady growth rate (Fig. 2g, h) indicates a lower (higher) formation rate of baroclinic instabilities over southern and western regions of Australia during PDRY (PWET), consistent with the large-scale rainfall changes. Hope et al. (2006) also link trends in baroclinicity and reduced frequency of passing troughs across the region with the observed rainfall decrease over SWWA. Here, we demonstrate that such changes can be driven by anomalous SST patterns over the Indian Ocean. The vertical thermal structure overlying warm SST anomalies at P2 in the central subtropical Indian Ocean in PDRY favors localized increases in convective activity, as seen in the increase in convective rainfall over SWWA and the reduction in large-scale rainfall. The asymmetry in convective rainfall response does not manifest itself in the rainfall distribution for WA, most likely due to the fact that with increasing distance inland, the impact of the warm SST at P2 giving rise to localized convective upward motion and enhanced convective rainfall in SWWA during PDRY is averaged away. On the other hand, both the circulation and thermal anomalies in PWET enhance widespread ascent of moist air masses associated with frontal movement, as evidenced by increases in large-scale precipitation in that ensemble set for both the SWWA and WA regions.

In summary, we have demonstrated that the Indian Ocean SST anomalies associated with dry/wet years over WA can themselves force significant anomalies in rainfall over the region. The SST anomaly fields involve both tropical and subtropical perturbations, combining to drive changes in atmospheric thickness, thermal winds, baroclinicity, and moisture advection onto the Western Australian coast. Future work will assess the relative roles of the tropical and subtropical SST anomalies in driving these rainfall changes and the lead times of predictability that may be involved.

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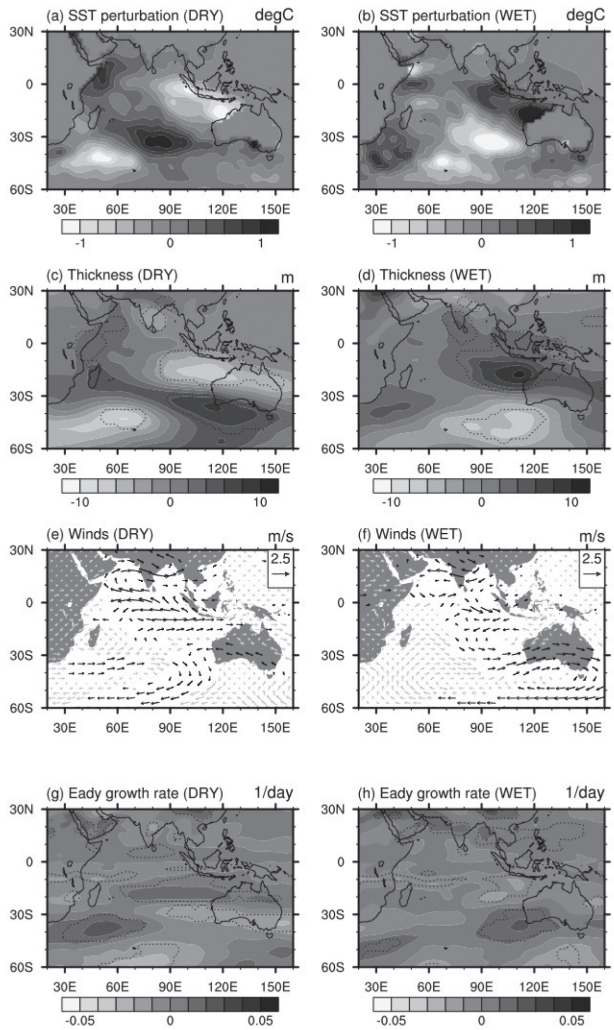

Figure 2. (a, b) SST perturbation (in °C), (c, d) thickness anomalies (in m for 1000-500 hPa), (e, f) wind anomalies at 500 hPa (in m s^{-1}), and (g, h) anomalies in Eady growth rate (in day^{-1}) averaged over the May-September period for the PDRY (left) and PWET (right) case, relative to the CNTRL. Dashed lines in (c, d, g, h) and black arrows in (e, f) indicate significant anomalies at the 90% confidence level as estimated by a two-tailed t-test. (adapted from Ummenhofer et al., 2007).

Comparison of the potential skill of raw and downscaled GCM output for river flow forecasting: a UK case study

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Hydrologic extremes (floods and droughts) are expected to become more commonplace under changing climatic conditions (Kundzewicz et al. 2007). These extremes can be very costly economically and to society as a whole. Skilful hydrological forecasts at a seasonal time-scale, defined here as 1 to 6 months, could potentially mitigate these harmful effects through advanced warning. This could aid water management decision making and increase human preparedness for extreme conditions. The need of research on the seasonal forecasting of river flows is becoming more apparent in the UK after the drought experienced in 2004-06, and the summer 2007 floods.

The aim of the work described here is to define a benchmark (or upper limit) in the potential skill of forecasting river flow using Global Climate Seasonal forecasts. The research is twofold: (1) Global Circulation Model (GCM) outputs are used directly in the form of re-analysis data, and (2) downscaled GCM precipitation is used to drive a hydrological model. The research focuses on the River Dyfi at Dyfi Bridge in West Wales, UK, a temperate basin of relatively small area (471.3 km^2) (Figure 1). The basin was chosen as it is near natural which implies that the climate-flow signal should be stronger than one with human influences. The Probability Distributed Model (PDM) was used to model the Dyfi river flows. PDM converts rainfall and potential evaporation (PE) to river flow at the basin outlet (Moore, 2007). Daily basin-averaged rainfall and PE and daily river flow data were used to calibrate (01/05/1980 to 30/04/1990) and evaluate (01/05/1991 to 30/04/2001) the PDM.

The input GCM data used are taken from ERA-40, which is a 45 year re-analysis of meteorological observations produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Uppala et al. 2005). The ERA-40 data was available at 2.5 ° x 2.5 ° and at a reduced 1.5 ° x 1.5 ° grid resolution. The re-analysis data at the closest land-based grid point to the Dyfi basin were extracted (52.5 °N 357 °E and 52.5 °N 357.5 °E for 1.5 ° and 2.5 ° resolution respectively). The stratiform and convective precipitation and snowfall were summed daily for

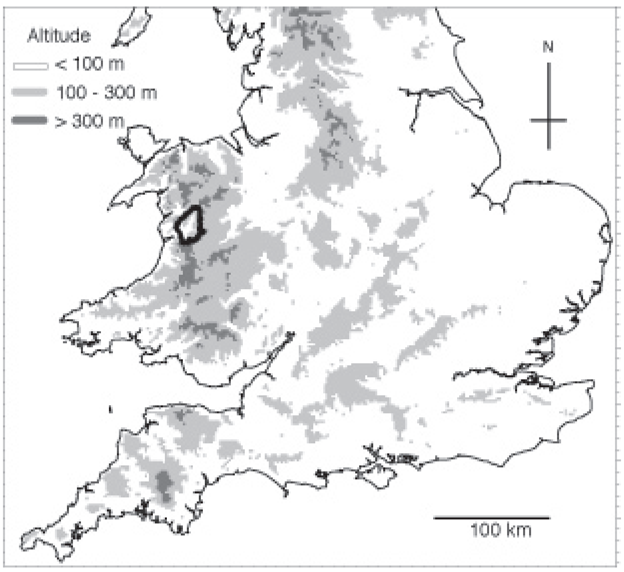

Figure 1: A map showing the south of England and Wales and the case study basin, the Dyfi at Dyfi Bridge (heavy line).

the grid points, and run through the PDM, whilst the PE data was left unchanged from the model calibration data set.

Owing to the coarser resolution of the ERA-40 data in comparison with the spatial scale of the river basin, the Statistical Downscaling Model (SDSM, Wilby et al. 2002) Version 4.1 was utilised to produce rainfall at the basin scale. Multiple linear regression models (one per month) were used to link large-scale atmospheric (ERA-40) predictors with basin scale rainfall (observed), and then a stochastic weather generator produced 10 downscaled daily rainfall series. The predictors were normalised prior to SDSM calibration over 01/05/1980 to 31/01/2002. Three predictor variables explained best the basin-scale rainfall at the two ERA-40 grid resolutions: geopotential (Z) at 500 hPa, zonal velocity (u) at 850 hPa and meridional velocity (v) at 850 hPa for 1.5 ° resolution, and Z at 500 hPa, u at 500 hPa and v at 850 hPa for 2.5 ° resolution.

The ability of GCM and downscaled GCM rainfall time series to reproduce river flow was assessed partially through the percent exceedance flow (QN). For example the Q5 value is the river flow which is equalled or exceeded 5 % of the time (high flow index), and the Q95 value is the river flow which is equalled or exceeded 95 % of the time (low flow index). The flow duration curves illustrating this information are shown in Figure 2 (page 22) (a) and (b). The simulated river flows driven by ERA-40 precipitation underestimate the simulated (from observed) flows. Input data at 1.5 ° resolution has slightly more accurate river flow estimates compared with 2.5 ° resolution, and this is also shown in the R2 values between observed and modelled flows (-0.143 and -0.238 for 1.5 ° and 2.5 ° resolutions) and the bias (-76.9 % and -82.0 % for Q95, and -72.6 % and -76.9 % for Q5 for resolutions 1.5 ° and 2.5 ° respectively). The negative bias stresses the underestimation of river flow using ERA-40 precipitation as direct input to the hydrological model, to be linked with the underestimated daily precipitation intensity by the GCMs. A possible explanation for the better representation by the 1.5 ° grid point is its closeness to the Dyfi basin compared with the 2.5 ° point.

The downscaling process on average increases the R2 value to 0.407 and 0.366 for resolutions 1.5 ° and 2.5 ° respectively. The flow duration curves show that the modelled river flow using downscaled rainfall series is closer to the evaluated flow (modelled flow from observations during the evaluation period, Figure 2 (a) and (b)). Average biases are -54.1 % and -49.8 % for Q95, and -25.9 % and -19.0 % for Q5 for 1.5 ° and 2.5 ° resolution respectively, which is a marked improvement compared with the earlier direct input of ERA-40 precipitation to the PDM.

The work aimed to define benchmark values for the potential skill of GCM seasonal forecasts for hydrological applications through the direct and downscaled use of GCM re-analysis data. The results at two spatial resolutions highlight that by using ERA-40 precipitation data as direct input to the PDM rainfall-runoff model, the simulated river flow substantially underestimates the observed river flow in the Dyfi basin. This is likely to be due to the inability of the ERA-40 assimilating model to resolve basin-scale (or GCM sub-grid scale) atmospheric processes such as orographic enhancement of rainfall over the Welsh Mountains, and precludes a direct operational use. With the help of a statistical downscaling technique (here SDSM), skills in river flow estimation are significantly improved for both the high and low flows. This pioneering work in Europe of river flow estimation from GCM outputs must be continued in comparing these benchmark results with seasonal GCM forecasts, such as those of the DEMETER multi-model ensemble climate data set as input to the PDM, and by the investigation of the use of different downscaling techniques.

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DEMETER–driven prediction of epidemic malaria in Africa: initial results from a continental–scale study

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Background

Epidemics of malaria occur when the disease attacks vulnerable populations with low immunity and are responsible for 155,000 to 310,000 deaths per year in Africa (Worrall et al., 2004). Epidemics may be triggered in areas of normally low transmission by a range of factors including abnormal meteorological conditions, changes in anti-malarial programs, population movement, and environmental changes (Nájera et al., 1998). As part of their global strategic plan for 2005-2015, Roll Back Malaria Partnership (RBM) includes the establishment and maintenance of early warning systems for malaria epidemics, in order to meet the target of 60% detected within two weeks and 60% responded to within two weeks of detection (RBM, 2005). As part of such a system, seasonal climate forecasts, when coupled with models of the disease, have the potential to enable malaria early warning with lead times of several months. Seasonal ensemble prediction system (EPS) forecasts of climate are skilful in some epidemic-prone African regions and the DEMETER seasonal EPS (Palmer et al., 2004) has previously been used successfully to drive a statistical rainfall-driven model for malaria prediction in Botswana (Thomson et al., 2006). As part of the AMMA (http://www.amma-international.org) and ENSEMBLES (http://www.ensembles-eu.org) projects, a process-based model of malaria, Liverpool Malaria Model (LMM, Hoshen and Morse, 2004), which simulates the complex relationship of the disease with climate, has now been coupled with the DEMETER multi-model seasonal ensemble forecasts. By employing a tier-2 approach (Morse et al., 2005) in which DEMETER-driven malaria model predictions are validated against ERA-40-driven model simulations, the requirement for observed malaria data is removed, enabling broad assessment of the potential of the seasonal forecasts for epidemic malaria prediction across Africa.

Coupling a process-based malaria model with a seasonal EPS

The practicalities of coupling a malaria model with a multi-model EPS on a continental scale are not straightforward. Health models are not generally designed for use over many locations or with multiple inputs and handling of many large EPS output files outside the proprietary visualisation and analysis software used by modelling centres can be cumbersome. A number of software tools have been created for data conversion and processing, running of the malaria model, and analysis of results, incorporating the facility of the University of Liverpool's state-of-the-art "MAP2" Beowulf cluster with the potential to make use of up to 900 nodes simultaneously (http://www.liv.ac.uk/physics/hep/Infrastructure/Computing.html). The software tools developed here are not restricted to malaria modelling and may be useful more generally for the coupling of EPS forecasts with application models.

The DEMETER multi-model reforecasts (Palmer et al., 2004) consist of output from a multi-model ensemble of seven different coupled AOGCMs each run with nine different sets of initial conditions. The full multi-model forecasts are available for four forecast start dates per year from 1980-2001 and extend to six months lead time. The ERA-40 reanalysis (Uppala et al., 2005) consists of 44 years of in-situ and remotely sensed data assimilated into a numerical weather prediction model to form a set of global analyses. In order to drive the malaria model with these datasets, temperature and precipitation fields from DEMETER and ERA-40 have been extracted from the ECMWF MARS data archive on a 2.5 degree grid consisting of 30 by 30 grid points from 37.5°N to 35.0°S and 20.0°W to 52.5°E, for the 22 years for which the full seven models are available from DEMETER (1980-2001).

DEMETER-driven ensemble malaria predictions are created by running the malaria model with each of the 63 DEMETER ensemble members as input. ERA-40 data are used to intialise the malaria model. Probabilistic malaria forecasts have been created in this initial assessment by equal weighting of the ensemble members. For each grid point, the ERA-40-driven and DEMETER-driven malaria simulations can be used to define low and high malaria events for the 22–year period (lower tercile, above the median and upper tercile) for three month windows (months 2-4 and 4-6) within each forecast integration period.

In order to assess the performance of DEMETER for malaria prediction, skill scores have been calculated for the DEMETER-driven malaria model forecasts using the ERA-40-driven forecasts as reference. Because the modelled process of malaria transmission exhibits a lag of between one and three months between rainfall and disease peaks, it is important to take into account any skill apparent in the DEMETER-driven forecasts which is in fact due to driving rainfall occurring during the initialisation period (i.e. the ERA-40 observations used as input before the start of the DEMETER forecast). This is an issue of concern for locations where the rainy season starts before the DEMETER forecast origin. Since the timing of the rains varies across the continent a general approach is required. This has been achieved by creating ERA-40-only malaria model forecasts, using the correct ERA-40 driver for the initialisation period followed by one of the 21 incorrect ERA-40 years for the forecast period. This process is repeated for each of the incorrect years as input in turn, generating a 21-member ensemble control forecast against which the performance of the DEMETER-driven forecasts are measured.

Skill of DEMETER-driven malaria simulations

Figure 1 (page 22) shows the increase in skill as measured by the ROC skill score (ROCSS) for the above the median event, relative to the skill obtained using the control run forecast. The scores are shown for the May forecast months 4-6 and November forecast months 4-6, corresponding approximately to the peak months for modelled malaria transmission in epidemic-prone regions of West and southern Africa respectively. A high variability condition on the ERA-40-driven malaria predictions (CoV>0.5) has been used to mask out grid points for which interannual variability is low and therefore attempt to focus on epidemic-prone areas, where interannual variability in transmission is high.

One issue that becomes clear when attempting to explain the skill or lack of skill shown in the plots is the need to understand the details of the transmission characteristics for any particular region. For example, there are very few skilful grid points apparent in West Africa for these two forecasts. Further investigation has revealed this is partially due to the positioning of the epidemic (high variability) fringe, which is further south by 2.5 to 5 degrees of latitude in the ERA-40 -driven malaria simulations compared to what is observed in other climate-derived maps (e.g. Craig et al., 1999) and to what is obtained with DEMETER.

In southern Africa DEMETER and ERA-40 patterns of variability are in closer agreement and the results shown in Figure 1 are more promising, especially for northern Zambia where some of the most skilful grid points lie. This is a region where temperatures are low enough to have a significant impact on malaria transmission, and where, as a result, a process-based model such as LMM has the potential to be particularly useful in capturing the non-linear climate-malaria relationship, and take advantage of the skill present in seasonal forecasts of temperature, which tends to be higher than the skill of rainfall predictions.

The results presented here need to be treated with some caution, however. A somewhat arbitrary condition has been applied to select high variability or “epidemic” areas and based on a climate-driven model, not on observed malaria variability. The malaria model employed here does not incorporate immunity and therefore is not suitable for use in high transmission (endemic) areas where immunity can be built up by the population and affect the dynamics of disease transmission. As a result any skill shown in Figure 1 cannot immediately be taken to represent skill in predicting real world malaria in these locations, but instead an indicator of potential skill of DEMETER in this region given a particular climate-malaria relationship.

Conclusions

Integration of application models with seasonal ensemble prediction systems is a complex process and one in which a cycle of implementation, assessment and improvement needs to be continually repeated. These initial results indicate the potential skill of the DEMETER forecasts for epidemic prediction areas of southern Africa, whilst also highlighting the difficulty in verification for West Africa against forecasts from a reference dataset which itself has not been extensively validated. Ongoing work will include thorough validation of ERA-40 against alternative gridded datasets for Africa, further refinement of pre- and post-processing techniques employed on the ensemble forecasts, and extension of the assessment to reforecast output from the ENSEMBLES project (http://www.ensembles-eu.org).

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The Southern Ocean Observing System (SOOS)

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The importance of the Southern Ocean to the global climate system and the uniqueness of its ecosystems are well known. The region is remote and logistically difficult to access and thus is one of the least sampled regions on the planet. Design and implementation of an observing system that encompasses physical, biogeochemical and ecological processes is therefore a formidable challenge.

Building on an initial Southern Ocean Observing System (SOOS) meeting in Hobart last year, a follow up meeting was held in Bremen this October (see: http://www.clivar.org/organization/southern/expertgroup/SOOS_workshop.htm). The aim of this meeting was to more fully develop the plans for such an observing system.

Thirty-two participants from backgrounds as diverse as physical oceanography, ecosystem studies and the tourist industry discussed various aspects of the observing system during the three days. The first day of the meeting consisted of a series of summary lectures and discussion about the SOOS structure. The second and third days saw attendees split into various groups to tackle different (though interconnected) aspects of the SOOS, for example (i) physics of ocean and atmosphere, (ii) ecosystems/biology, (iii) biogeochemisty/carbon and (iv) cryosphere and sea ice. During this time they looked at the main science questions that any hypothetical observing system should aim to answer and the types of measurements that would be needed in order to do so. The state of the observing system and gaps were also examined. Cross group interaction was actively encouraged and each group reported back on progress at regular intervals.

A plan for production of a SOOS document, with lead authors identified as responsible for writing sections, and identifying others to do so, was drawn up. This will be worked on over the next few months, with the idea that a near final draft document will be openly discussed at the SCAR/IASC Open Science Conference being held in St Petersburg in July 2008.

The fourth session of the CLIVAR/GOOS Indian Ocean Panel

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The fourth session of the CLIVAR/GOOS Indian Ocean Panel (IOP) took place on 23-25 April 2007, kindly hosted by the South Africa Weather Service (SAWS), in Pretoria, South Africa. The SAWS issues rainfall and temperature forecasts at various time ranges, including the seasonal-to-interannual time scale. SAWS has recently started to issue probabilistic forecasts of extremely dry/wet and hot/cold conditions. It was successful in predicting high probabilities of dry and hot conditions over South Africa during the 2006/07 austral summer season. This season coincided with an El Niño event, and the various models used by the SAWS to compile a seasonal forecast were in strong agreement that the main summer season would in all likelihood be dry.

The IOP took the opportunity to review the impacts of Indian Ocean variability on African climate systems, recognizing strong connections between precipitation anomalies over the continent and the modes of interannual SST variability of the Indian Ocean, such as the Indian Ocean Dipole (IOD) and the subtropical dipole mode. Several science talks, given by African scientists, focused on the well known impact of the Indian Ocean dipole on the short rains (Oct/Nov/Dec) over equatorial East Africa and the less well known (and weaker) opposite signed rainfall impact over subtropical south-eastern Africa. For Madagascar, the 2006-7 summer season was one of the most devastating over the last decade in terms of losses in lives and impacts on infrastructures and agriculture. During this period positive SST anomalies were observed in the Indian Ocean northeast of the island, in the Mozambique Channel and to the south of Madagascar. The influence of these climate modes on African rainfall variability are an important issue to be understood in cooperation with the CLIVAR Variability of the African Climate System (VACS) panel.

The IOP reviewed the development of the sustained observing system in the Indian Ocean, called IndOOS (Indian Ocean Observing System). The key new component of IndOOS is the tropical moored buoy array and its integration with other observational platforms, including Argo floats, Volunteer Observing Ship XBT/XCTD sections, surface drifting buoys, and the tide gauge network, as well as satellite observations. An IndOOS Data Portal site has been set up at http://www.incois.gov.in/Incois/iogoos/home_indoos.jsp. All the available in situ observation data for IndOOS are listed with the link to data providers. Satellite derived gridded variables are also available through the live access server. Up to April 2007, 15 sites in the tropical mooring array have been occupied, representing 32% of the total 47 sites in the proposed array. The numbers of deployed Argo and surface drifting buoys in the Indian Ocean are closely reaching the planned coverage density, although a commitment to maintain coverage in the long term remains to be developed. During the next few years, JAMSTEC (Japan) will maintain two TRITON moorings and an ADCP near the equator at 90-95°E. NOAA (USA) will maintain eight ATLAS moorings at 1.5°N, 0°, and 1.5°S along 80.5°E; 8°N, 4°N, 1.5°N and 0° along 90°E; 8°S at 67°E, and an ADCP near 0°, 80°E. In addition, NOAA (USA) will expand from 8 to 12 ATLAS moorings in the eastern Indian Ocean and will deploy a subsurface ADCP moored array south of Sri Lanka in the coming year through international partnerships. MoES (India) will maintain three moorings on the equator at 77°, 83° and 93°E and will expand the ADCP array to the north and south (1.5°N/S) at 77 and 93°E. FIO (China) and AMFR (Indonesia) will deploy a new ADCP mooring near 8.5°S, 160.75°E. Fishing vandalism continues to be a strong concern for the moored buoy array. Data return for ATLAS and TRITON moorings combined was 68% for the period October 2004 to March 2007, and it is expected that the value will diminish with time because there are several moorings presently not transmitting data. Ship time also remains a concern since there is no systematic framework for planning cruises on a regular basis, not only for the mooring array but also for Argo and surface drifter buoys. The Panel recognizes the necessity of establishing a "resource board" for the Indian Ocean to provide resources such as ship time for further development of IndOOS, especially for the mooring array development. The Panel has asked the Indian Ocean GOOS Regional Alliance to convene a second high level review of IndOOS at its next annual meeting in December 2007 to assess progress since the first review in 2005. The review panel will be asked to consider formation of the resource board.

The panel reviewed the outcomes of two recent research vessel based process studies in the area: Vasco-Cirene and MISMO. These had both been successfully completed to provide a significant amount of in situ observational data, which are now being extensively analyzed among the scientists involved. The Vasco-Cirene experiment in January/February 2007 was conducted to provide in situ observations of oceanic and atmospheric variability, as well as air-sea fluxes, over the thermocline ridge between 5oS and 10oS in the western Indian Ocean. Although a strong intraseasonal disturbance was not observed during the experiment, invaluable data on cyclogenesis were obtained by a new observation platform, called Aeroclipper. The MISMO experiment during October to December 2006 took place in the central/eastern equatorial Indian Ocean to capture the atmospheric and oceanic variations associated with MJO initiation and passage. The observations captured development of MJO convection and eastward movement of large-scale cloud systems. Ocean variability at the intraseasonal time-scale demonstrated the strong upwelling (>10m/day) and associated variations in the chlorophyll concentration in the thermocline level. The scientific leaders of Vasco-Cirene and MISMO were invited speakers at the IUGG Symposium on Dynamics of Convectively-Coupled Equatorial Waves and the Madden-Julian Oscillation (Italy, 2007) and 22 talks were presented on the preliminary cruise results

The Panel reviewed a white paper on "monitoring the Agulhas Current" by L.Beal et al. and recognized that the western subtropical region is the weak link of IndOOS. The scientific rationale for long term measurement of the Agulhas is to improve understanding and modelling of its dynamics and its role in inter-ocean exchange (Indian to Atlantic) as it relates to the global overturning circulation. The attractive aspect of the proposal set out in the white paper is the staged approach, building up the monitoring effort through a series of process studies with coordination of resources across three projects involving international collaboration. At the present time there are not many Argo floats in this region, the repeat hydrographic sections are insufficient, and satellite data do not provide vertical structure directly, leaving the Agulhas Current the least known of all the western boundary currents. The proposed measurements will, in the first stage, address connectivity of the Agulhas in the region where it is strongest to major currents at lower latitudes and the eddy field. Generally, the Agulhas measurements will provide very useful in situ data, which can also be used for model evaluation and improvement. The Panel strongly recommended that the proposed pilot studies should go forward.

Attendees at the recent IOP4 meeting

Finally the panel discussed possible future research directions IOP should take. Considering the rapid growth of IndOOS, quantitative analyses using observed data will be a key research area:

- *Intraseasonal oscillations (ISOs).* The CLIVAR Asian-Australian Monsoon Panel (AAMP) has noted on many occasions that ISOs form the building block of the monsoons and are potentially a key to improved seasonal climate prediction. The tropical mooring array developed by the IOP provides a new stream of data that not only reveals the role of the ocean in this phenomenon, and potentially improves modelling of the ISO, but also improves the weather observing system in the region. The moorings will be extremely valuable to data assimilation for weather forecasting and reanalysis efforts. At present there are few such measurements in the Indian Ocean and this lack of information prevents accurate initial condition determination of weather forecasts and limits reanalysis efforts.
- *Mixed-layer heat budgets.* A few examples of quantitative mixed layer temperature (MLT) analysis in the Indian Ocean highlighted the difference in the regime of seasonal heat balance in the southeast Indian Ocean and the effect of the barrier layer. On-going work on the Indian-Ocean MLT budget using an ECCO assimilation product shows that the point-wise balance near the eastern node of the IOZM/IOD is different for the 1994 and 1997 events in terms of the role of surface heat flux, zonal advection, and vertical diffusion. The balance at 4.8^{o}S, 101^{o}E has some substantial differences from that at 0^{o}N, 97^{o}E. The utility of data assimilation products to analyze MLT balance can be extended to the analysis of upper-ocean heat budget in general, and for longer time scales, e.g., to address questions related to the multi-decadal warming of the upper Indian Ocean.
- *Validation of air-sea fluxes.* SST in the Indian Ocean has been rising in recent decades. Air-sea fluxes of momentum, heat, and freshwater, being intimately coupled to SST, have also shown long-term trends. It is found, however, that a reliable quantification of the magnitude of the trends is difficult to obtain due to large uncertainties in climate flux datasets. Though only available at limited locations and for limited periods, the flux buoy time series obtained from the integrated Indian Ocean Observing System (IndOOS), have already demonstrated their value in identifying biases in flux data products, analyzing upper ocean heat budgets at intraseasonal, seasonal, and now to internnual timescales, and improving the understanding of key air-sea coupling issues in the Indian Ocean.
- *Predictability/prediction studies of the significant climate modes in the Indian Ocean, such as IOD.* Experimental seasonal predictability/prediction studies are ongoing at several institutions using coupled GCMs. How ENSO and IOD climate modes interact with each other and/or how they influence the other phenomenon are key issues to be understood for better seasonal prediction not only within the Indian Ocean but also for the global climate system. This provides strong rationale for IndOOS. IOP and AAMP are discussing the possibility of a coordinated study and intercomparison of the predictions of the 2006 and 2007 IOD events by the FRCGC (JAMSTEC), GFDL (NOAA) and BMRC (Australia) coupled models. These years are interesting because all models agree in predicting the strong positive event in 2006 and they disagree markedly

in predictions for 2007. A case study of the successes and differences can lead to model improvement.

- *Detection and understanding of the decadal and inter-decadal time-scale variability*. In addition to substantial and socially-relevant intraseasonal to interannual variability, the Indian Ocean exhibits – in models and observations – changes on longer timescales, from decadal to climate change. The decadal and inter-decadal timescale variability remains to be fully documented and understood, and the extent to which it acts to modulate variability on shorter timescales is still an open research question. Further, the detection of radiatively-forced trends is limited by the presence of this decadal variability. Finally, the potential predictability of these decadal variations has begun to be explored using coupled modelling experiments. The IOP has a vision of sustained observing in this region, and based on recent studies of decadal and longer term variation of the Indian Ocean, the panel is convinced that an important societal benefit of IndOOS will emerge from future studies of climate change. Recent papers on long term variations by panel members and collaborators include:

Schoenefeldt, R., and F.A. Schott, 2006: Decadal variability of the Indian Ocean cross-equatorial exchange in SODA. *Geophysical Research Letters* **33** (8): Art. No. L08602 APR 20 2006.

Chang P, T. Yamagata, P. Schopf, et al., 2006: Climate fluctuations of tropical coupled systems - The role of ocean dynamics JOURNAL OF CLIMATE 19 (20): 5122-5174 OCT 15 2006.

Alory, G., S. Wijffels, and G. Meyers G, 2007: Observed temperature trends in the Indian Ocean over 1960-1999 and associated mechanisms *Geophysical Research Letters* **34** (2): Art. No. L02606 JAN 20 2007.

Yu, L-S.. and R.A. Weller, 2007: Objectively analyzed air-sea heat fluxes for the global ice-free oceans. *Bulletin of the American Meteorological Society* **88** (4): 527-+ APR 2007

Lee, T. and M.J. McPhaden, 2007: Decadal Phase Change in Large-scale Sea Level and Winds in the Indo-Pacific Region at the end of the 20^th Century. Submitted to Geophysical Research Letters.

More information on the activities of the CLIVAR/GOOS Indian Ocean Panel can be found at: http://www.clivar.org/organization/indian/indian.php

Summary of the 11th Session of the Working Group on Seasonal to Interannual Prediction (WGSIP)

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The 11th session of WGSIP took place on 7-8 June 2007, immediately after the WCRP Workshop on Seasonal Prediction held at the World Trade Centre in Barcelona, Spain. This had several advantages, notably the presence of several distinguished visitors on the first afternoon to provide perspectives from WCRP, the JSC and the CLIVAR SSG, and the necessity to deal with matters concisely, so as to fit the meeting within the scheduled 1.5 days. We would like to acknowledge our hosts from the Meteorological Service of Catalonia, who generously provided facilities for the WGSIP meeting in addition to their support for the Seasonal Prediction Workshop itself.

The following is a summary of the topics discussed at the meeting, covering both current and future WGSIP activities:

WCRP Workshop on Seasonal Prediction
The Workshop (see Kirtman & Pirani, in this issue for an overview and recommendations resulting from the Workshop) was held on 4-7 June 2007 hosted by the Catalonian Meteorological Service. It was organised by the WCRP Task Force on Seasonal Prediction (TFSP) in collaboration with the core programs of the WCRP (CLIVAR, CliC, SPARC and GEWEX) and the WMO World Climate Programme (WCP). The Workshop was also co-sponsored by the Climate Information and Prediction Services (CLIPS) Project of the WMO WCP, the European Science Foundation (ESF), the Spanish Ministry of Science, the School of Physics of the University of Barcelona, the Catalan Water Agency, US CLIVAR, the US National Science Foundation (NSF), the US National Aeronautics and Space Administration (NASA) and the US National Oceanic and Atmospheric Administration (NOAA). Attendance was very high and the Workshop was hailed a success, with around 180 people coming from over 30 countries.

The WCRP Task Force on Seasonal Prediction (TFSP)
The planned two year life time of the TFSP came to an end with the Barcelona Workshop and its mandate will continue to function through the WGSIP. The TFSP, which drew on expertise from all the WCRP core projects (CLIVAR, CliC, SPARC, and GEWEX), WGNE and WGCM, together with the Sea Level Task Team, pioneered the WCRP coordinated strategy initiated in 2005. The TFSP provided a mechanism that did not previously exist to evaluate potential predictability in the cryosphere, biosphere, stratosphere and the rest of the fully coupled climate system, while also delivering focus on the value to society of seasonal prediction.

WGSIP has assumed the leadership of the TFSP Experiment (see www.clivar.org/organization/wgsip/tfps.php for more details). The TFSP Seasonal Prediction Workshop sessions organised by the different WCRP Projects gave an overview of what is currently known on the potential predictability to be gained from including more Earth system coupled processes in seasonal forecasting. An outcome of the Workshop was that, in addition to the baseline TFSP Experiment design, there is plenty of scope for further sensitivity studies addressing stratospheric, land surface and cryospheric processes.

WCRP Decadal Prediction Cross-Cutting Activity
WGSIP discussed the new decadal prediction cross-cutting activity that was endorsed by the 28th Session of the WCRP JSC. WGSIP agreed to take co-leadership of this activity with WGCM, as recommended by the JSC. As an initial step the technical aspects of decadal prediction experiments, such as the best initialisation of an ocean model from analyses, will be addressed. Climate change is inextricably part of seasonal forecast calibration and the problem of recovering observed trends. Processes, for example aerosols, that are mainstream in the climate community need to be incorporated into seasonal prediction. The concept of testing climate change models in seasonal prediction mode has been endorsed by the climate community (see next section). Given the large number of overlapping issues, it was clear that WGSIP and WGCM need to work more closely together. One suggestion to be explored is the possibility of a joint mini-workshop on decadal prediction. The CLIVAR basin panels and the Global Synthesis and Observations (GSOP) Panel also need to be involved in the ocean initialisation problem.

Climate Model Validation
WGISP reviewed the value of testing "climate change" models using seasonal integrations. There are two aspects to this, the first related to model biases. Coupled integrations that are initialised as close to reality as possible can be evaluated

more exactly against observations in terms of degree of model drift and the evolution of errors, than longer runs which are supposed to represent "mean climate". Model integrations are needed only over the appropriate timescales: some biases are inherent in just the atmosphere model and develop within a few days, whilst other biases involving coupled feedbacks develop over a period of months to a year. Of course, there may be other biases related to slow processes in the climate system, which are not addressed by seasonal timescale integrations. A second aspect of testing climate models with seasonal integrations is to look at ENSO forecast skill (and perhaps seasonal forecast skill in general). The first aspect is particularly helpful in the development phase of climate models, since the modest integration time allows rapid turnaround of experiments. The second aspect may be helpful in deriving metrics to help judge the credibility of projected changes in ENSO and dynamically forced regional climate change.

Several strategies for developing these ideas further were discussed. The first is to ensure that as many "IPCC" class models as possible take part in the TFSP experimentation. This was one of the original hopes behind the development of the TFSP plans, and WGSIP encourage as many groups as feel able to participate in this experiment. A separate strategy is the concept of developing some written guidance on simple but effective ways of initialising and testing coupled models in seasonal forecast mode. The guidance would be targeted in particular at those groups who do not have access to suitable ocean initial conditions, and might be particularly helpful during the development phase of models.

Seasonal Prediction Applications

The importance of data availability and accessibility for seasonal prediction applications users was discussed. Daily data would be of considerable use, or better still real time data, even if they could be provided only for a limited number of grid points in the public domain. If real time data cannot be released then a compromise is needed to show the range of forecast products that are available. If forecasts are provided to the user, they must also be provided with the model climate, the predictability, forecast quality, for example a reproducibility index, and the skill of the ensemble compared to the model climate. Feedback is, in turn, necessary from users to the forecasting community to develop tailored products, such as histograms of break cycles and the fact that users are generally more interested in intraseasonal variability instead of monthly totals. User development and capacity building is necessary and could be directed through the CLIVAR regional panels. A link needs to be made with decision makers, with information needing to be made more publicly available.

For more information on WGSIP activities refer to www.clivar.org/organization/wgsip/wgsip.php

Attendees at the recent WGSIP meeting

New ocean atlases – Volume 2 now ready

The CLIVAR project office at NOCS is about to issue the second volume (Pacific Ocean) of the atlases describing the measurements made during the 1990-1997 World Ocean Circulation Experiment (WOCE). The series of 4 volumes, (Southern Ocean (published in 2004), Indian and Atlantic still being prepared) contains vertical, trans-ocean sections, horizontal maps and property-property plots of up to 15 physical and chemical variables.

The Pacific Atlas has been compiled by Prof. Lynne Talley of Scripps Institution of Oceanography. Drs Mike Sparrow and John Gould formerly of the CLIVAR Project Office, are members of the editorial team (along with Dr Piers Chapman) that has produced the atlases. The printing of 800 copies that will be distributed worldwide was funded by a grant from BP.

Details of the atlases can be found at <http://www.woce.org/atlas_webpage.

For further information contact John Gould (wjg@noc.soton.ac.uk) or Mike Sparrow (mds68@cam.ac.uk)

Exchanges 44: Call for Submissions: Theme: "Furthering the Science of Ocean Climate Modelling"

CLIVAR Exchanges solicits articles for the January 2008 edition that highlights issues associated with using ocean and ocean-ice models for global climate studies and observational reanalysis. Of special interest will be articles that discuss the use of ocean and ocean-ice models for understanding the ocean climate system, including the experimental design of the simulations, such as boundary conditions, initial conditions, forcing datasets, bulk formulae, etc. Articles featuring recent numerical algorithm and physical parameterization issues especially relevant to the problems of running models for global simulations, are also solicited.

The guest editors will be Stephen Griffies (GFDL) and Helene Banks (Met Office Hadley Centre). The closing date for submissions is Friday November 30th 2007.

Please see http://www.clivar.org/publications/exchanges/guidel.php for guidlines for submitting articles.

Contents

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