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Understanding and Predicting Seasonal-to-Interannual Climate Variability - The Producer Perspective

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Abstract

Seasonal prediction is based on changes in the probability of weather statistics due to changes in slowly varying forcings such as sea-surface temperature anomalies, most notably those associated with El Niño–Southern Oscillation (ENSO). However, seasonal weather can be perturbed by many factors, and is very much influenced by internal variability of the atmosphere, so comprehensive models are needed to identify what can be predicted. The predictability and probabilistic nature of seasonal forecasts is explained with suitable examples. Current capabilities for seasonal prediction that have grown out of work done in the research community at both national and international levels are described. Dynamical seasonal prediction systems are operational or quasi-operational at a number of forecasting centres around the world. Requirements for seasonal prediction include initial conditions, particularly for the upper ocean but also other parts of the climate system; high quality models of the ocean-atmosphere-land system; and data for verification and calibration. The wider context of seasonal prediction and seamless forecasting is explained. Recommendations for the future of seasonal prediction and climate services are given.

.*Keywords:* Sources of predictability; forecast methods and formats; international coordination; health monitoring and surveillance

1. Scientific underpinnings for seasonal prediction

1.1. Sources of predictability on seasonal-to-interannual timescales

Accurate, deterministic predictions of the weather are only possible for a limited number of days into the future. The exact limit will depend on the scales being predicted, the predictability characteristics of the atmospheric flow at the time of prediction and the accuracy with which the initial conditions can be ascertained, but for times which are weeks and months into the future, meaningful deterministic forecasts of daily weather are not possible. At these longer timescales, probabilistic forecasts of weather and weather patterns are all that can be attempted.

Seasonal forecasting is the prediction of the climate of forthcoming seasons, and in particular the extent to which the expected climate differs from the climate of previous years. In principle, climate encompasses everything – number of rain days, expected risk of heatwaves, number of frost days etc. – as well as simple statistics such as seasonal mean temperature or precipitation. If there is no reason to think that the forthcoming season should be different from the past, then a forecast of climatology can reasonably be given: the distribution of possible outcomes is expected to match what has been observed in the past. However, the climate is often perturbed in predictable ways by various factors, and it is these perturbations to the distribution of possible outcomes which are the basis for and target of seasonal forecasting.

Two factors should be borne in mind in the following discussion. In many cases the distribution of possible outcomes for a coming season is still quite large, and will often have substantial overlap with the climatological distribution of outcomes. Seasonal forecasting of specific outcomes, even for seasonal mean values, is inherently probabilistic. Another factor to bear in mind is that although the discussion in this paper almost entirely concerns simple seasonal mean statistics, the same factors that act to increase seasonal mean rainfall or temperature, also act to change the distributions of more detailed statistics, such as the length of dry spells or number of hot days. There is thus the potential for a wide range of applications of seasonal forecasts, where skill exists.

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1.1.1. Forcings external to the climate system

Volcanoes and solar variations have been recurring themes historically in discussions of seasonal prediction. Variations in solar forcing are, however, generally comparatively small and tend to operate on long timescales with the most notable being the 11-year solar cycle. Van Loon et al. [1] review some aspects of solar forcing but the deduced effects are not strong on seasonal timescales. Volcanoes, on the other hand, clearly affect climate (for example, Robock,[2]; Stenchikov et al.[3]) and have the potential to add skill to certain seasonal forecasts made after large eruptions. However, Collins [4], in a study of the effects of the El Chichón and Pinatubo eruptions, notes that "the volcanic signal is only robust on the spatial scale of continents and, moreover, the signal can easily be contaminated or completely obscured by climate variability".

Anthropogenic forcing effects from greenhouse gases and aerosols are often neglected in seasonal prediction with the presumption that the effects are small compared to natural variability and that the global warming signal is, in any case, largely incorporated into the forecast in the initial and boundary conditions. However, Liniger et al. [5] and Boer [6] show that specification of anthropogenic forcing does influence seasonal forecasts, and the time-variation of greenhouse gas and aerosol forcing are now increasingly being introduced into seasonal prediction schemes.

1.1.2. Predictability from internal variability of the climate system

The natural workings of the climate system give rise to internally generated variability on all timescales. Some of the processes, such as the development of synoptic systems in the atmosphere, happen on short timescales, and are simply a source of unpredictable noise for seasonal prediction. However, slow variations of the climate system are often a source of predictability on seasonal timescales. Examples include the longer timescales of the ocean and the coupled atmosphere–ocean system, and also other components such as sea ice, soil conditions, snow cover and perhaps the Quasi-Biennial Oscillation (QBO) and the state of the stratosphere.

The most important source of seasonal predictability is El Niňo and the Southern Oscillation. Walker [7][8] detected a see-saw between the sea level pressure at Tahiti and Darwin, known as the Southern Oscillation (SO) that was later linked to variations in equatorial sea-surface temperature in the eastern Pacific by Bjerknes [9]. This combined ocean–atmosphere ENSO phenomenon is the dominant mode of Earth's interannual climate variability, and its associated global teleconnections produce important temperature and precipitation anomalies across the globe (for example, Ropelewski and Halpert [10]; Rasmusson and Carpenter [11]). The prediction of ENSO variability with a simple coupled ocean–atmosphere dynamical model was first demonstrated by Zebiak and Cane [12]. Subsequent work has led to the development of today's sophisticated operational ENSO forecast systems using coupled ocean–atmosphere General Circulation Models (GCMs).

Oceanic anomalies other than ENSO can also drive temperature and precipitation anomalies on seasonal timescales (for example, Goddard et al. [13]; Cassou et al.[14]), including the connection of the tropical Atlantic with North-east Brazil rainfall.[15][16] the tropical Indian Ocean.[17][18] and the extra-tropical Atlantic (for example, Rodwell and Folland,[19]). Land surface processes have the potential to provide a signal on seasonal timescales, at least in some areas and under some circumstances (for example, Koster et al, [20]; Senevirante et al, [21]) and anomalous snow cover/amount may also have an effect (for example, Fletcher et al..[22] and references therein).

Other phenomena that vary on seasonal timescales may be identified in the system and may enhance (or detract from) predictive skill depending on how they are invoked and treated in the forecast procedure. They include the Northern Annular and Southern Annular modes (NAM and SAM), the Pacific North American (PNA) pattern and the North Atlantic Oscillation or NAO, (Hurrell et al.[23] Bojariu and Gimeno [24], among others). These latter are generally thought to be internal dynamical modes of the atmosphere, but with the potential sometimes to act as mediators of seasonal predictability. In some cases the links back to oceanic forcing are clear, in others less so. Much of the variability of the modes may in any case be unpredictable.

Recent investigations also suggest that the stratospheric may prefigure and affect tropospheric anomalies (for example, Baldwin and Dunkerton [25]; Ineson and Scaife [26]). The long timescales of the stratospheric QBO could also have an effect under some circumstances (for example, Boer and Hamilton [27]; Marshall and Scaife [28]).

1.2 Predictability and the probabilistic nature of seasonal forecasts

The mechanisms mentioned above, as well as others implicit in complex coupled atmosphere–land–ocean models, offer the possibility of a predictable signal on seasonal timescales. However, a predictable signal always co-exists with unpredictable noise in the seasonal forecasts, due to the effects of synoptic activity and/or other sources of unpredictability. The fraction of the total variance accounted for by the signal component is generally modest, and thus so is the predictability, particularly away from the tropics. Given the limited predictability, it is generally most appropriate to characterize a forecast in terms of a probability distribution. While a deterministic forecast essentially assigns a probability of 1 to a particular forecast result, a probabilistic forecast also indicates the uncertainty of the result.

Probabilistic forecasts can be produced in various ways. For dynamical seasonal forecasting systems, the starting point is an ensemble of forecasts Y_i, $i = 1 \ldots n$, produced using a set of initial conditions that are intended to reflect the uncertainty in these conditions. The forecasts follow different evolutions because of their differing initial conditions, resulting in a spread of trajectories at forecast time. If the trajectories spread apart widely, the inferred probability distribution is also wide and the forecast is uncertain, while a bundle of close trajectories might suggest less uncertainty. However, this neglects error in the forward calculation of the model. Experience has shown that dynamical seasonal forecast models are overconfident – their spread is too narrow to match the range of observed outcomes – and there is often little relationship between ensemble spread and the error in the forecast. The reason for this is believed to be large model error. Multi-model approaches, where ensembles from different state-of-the-art models are combined thereby implicitly averaging out some of the model errors, generally produce more skilful forecasts than do the results from a single model [29][30]. Multi-model systems are becoming more of a feature of operational seasonal forecasting as noted in Section 4.2.

A probabilistic forecast may be characterized by the full probability distribution or by giving the probabilities of Y falling into various categories (probability that Y is above normal is p_A, near normal, p_N, below normal p_B). Alternatively, an ensemble mean and standard deviation can be given. Converting the ensemble distribution of the output of an imperfect model into a credible probability distribution requires a careful assessment of the expected impact of model error on the forecasts, which is difficult because of the very limited number of past cases available for analysis. Probabilistic forecasts can also be created directly from statistical analysis of empirical or model-based predictors.

Predictability and forecast skill are both functions of the state of the system and of geographic location. Skill is generally higher in the extreme phases of ENSO than on average, for instance. Studies in which the observed sea-surface temperatures (SSTs) are specified as boundary conditions for atmospheric models, which then determine both local and remote responses, give some information on the forced component that results from boundary forcing of this kind. For SST forcing, the potential predictability is largest in the tropics where natural variability is comparatively low and the atmosphere responds reasonably directly to the SSTs [31], and decreases towards middle to high latitudes where natural variability is high and the signal from the tropical SSTs is attenuated (for example, Rowell [32]; Zwiers and Kharin [33]; Kumar et al. [34]). Actual forecasts rarely attain the skill implied by idealized studies, a skill that over land and for mid-latitudes is often modest itself. It is vital, therefore that seasonal forecasts be accompanied by a measure of expected forecast skill, based on the past operation of the system, in order to be properly utilized.

Seasonal prediction is a challenging field of research and application since predictability varies with time and location and the predictable signal is often masked by natural variability. Improvements in forecast procedures and in forecast skill are evolutionary in nature and depend on continuing efforts to better observe, analyse, model and predict the complex coupled climate system and to provide forecasts to users in ways that are economically and socially valuable. Despite the difficulties, the skill and value of seasonal forecasts promise to increase as investments are continued in the various components of the observation-analysis-prediction-application system.

1.3 Presently achieved skill of general circulation model forecasts

The most successfully predicted large-scale phenomenon on seasonal-to-interannual scales is ENSO, and it influences worldwide climate far beyond the tropical Pacific. An ENSO prediction is thus the starting point for assessment of seasonal prediction models. The NINO3.4 SST anomaly (an area average over 5N-5S, 170-120W) is the index most often used to quantify ENSO. The Mean Square Skill Score (MSSS) is adopted as the measure of deterministic skill of NINO3.4 SST forecasts in the WMO Standardized Verification System for Long-Range Forecasting (SVS-LRF) [35]. Other skill measures which are often used are the temporal correlation coefficient (TCC) and root-mean-squared error (RMSE). Skill is almost always assessed by looking at the bias-corrected forecasts rather than the raw model output.

Forecast skill is usually highest when considering multi-model ensemble (MME) forecasts, created by combining forecasts from several different models. As an example of achievable skill, the MME forecast from the European DEMETER (Development of a European Multimodel Ensemble system for seasonal to inTERannual prediction) project [29] has a TCC skill of 0.89 for 3-month lead prediction of the seasonally averaged NINO3.4 SST anomaly, with almost all the single coupled models' TCCs over 0.8, when assessed using hindcasts for the period 1980–2001. Jin et al. [36] created a larger ensemble by including 3 additional models from the Asia Pacific Economic Cooperation Climate Center (APCC) Climate Prediction and its Societal Application (CliPAS) project, giving a total of 10 models. They show that the MME again outperforms all of the individual models (Figure 1.). The ENSO prediction skill often shows a dependence on the seasonal cycle, with SST changes in the May-June period being particularly hard to predict (for example, Saha et al. [37]). This is a time of year when persistence of anomalies is particularly poor, and although the best models may suffer some loss of skill, their advantage over persistence is actually at a maximum (for example, Wang et al. [30]).

Progress in the skill of ENSO forecast systems can be assessed by comparing the skill of successive operational systems over a common set of hindcasts. Figure 2 shows this for the three European Centre for Medium-Range Weather Forecasts (ECMWF) operational forecast systems which have been implemented during the last decade or so. Progress is steady, and predictability estimates (not shown) suggest there is still much improvement to be made in the years ahead.

Although most emphasis is given to ENSO SST predictions at relatively short lead times (up to six months, say), it is worth noting that many systems have considerable skill at longer timescales. For instance, the 12-month-lead mean TCC from an early MME study was reported as 0.63 [38], and the SINTEX-F TCC skill reaches 0.6 at month 16 and 0.5 at month 24 for the 5-month running mean NINO3.4 SST anomaly [39].

Moving beyond ENSO forecasts, the practical qualities of seasonal forecasts are often assessed by looking at skill scores for surface (2m) air temperature and precipitation. Skill is again calculated for anomalies (or occasionally standardized anomalies) after calibration for model biases.

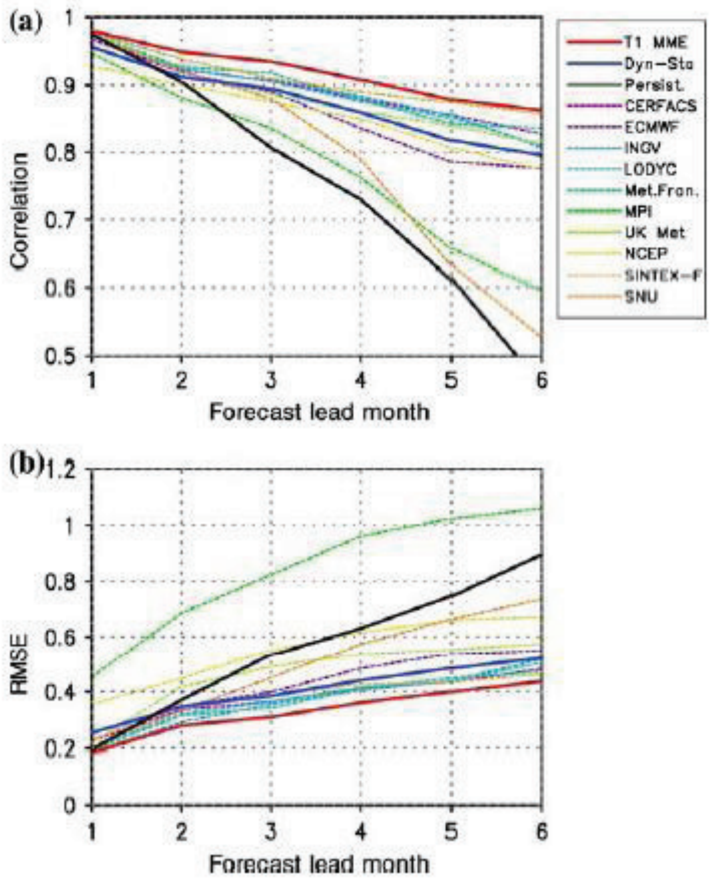

Figure 1. NINO3.4 forecast skill for a multi-model ensemble (Source: Jin et al. [36])

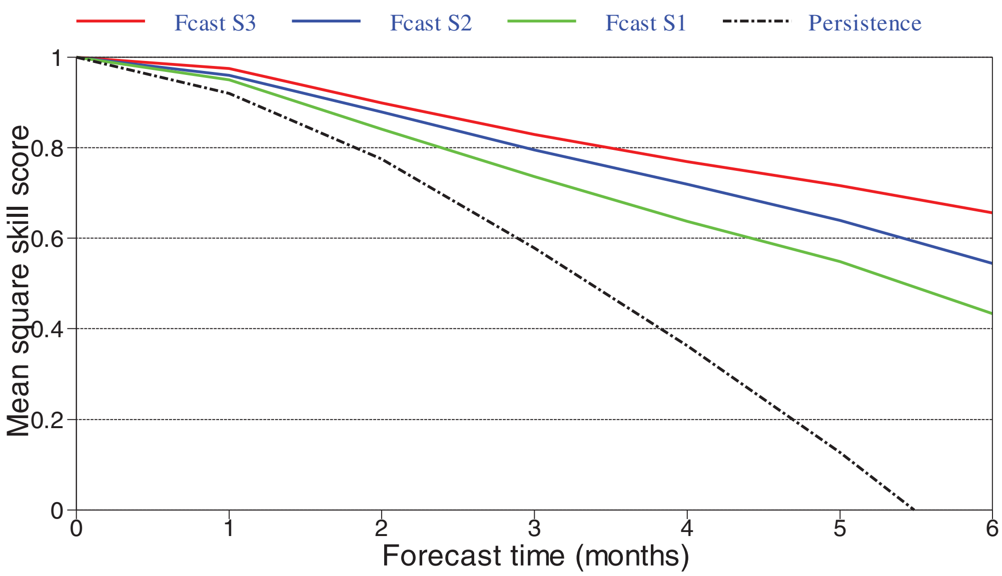

Figure 2. NINO3.4 SST MSSS from three operational systems at ECMWF, introduced in 1997 (green), 2002 (blue) and 2007 (red), assessed over a common period of 1987–2002

Results from the CliPAS project using a total of 14 models [30] show that 1-month lead MME hindcasts during 1981–2003 have statistically significant TCC skills over about 0.5 for seasonal mean surface air temperature and precipitation anomalies over some tropical land areas and much of the tropical oceans. Extra-tropical areas with statistically significant TCC skills are rather limited and somewhat patchy over land. Analysis of the National Centers for Environmental Prediction (NCEP) forecasting system [37] shows that surface air temperature and precipitation TCCs for monthly mean anomalies, averaged over all northern hemisphere extra-tropical land points, decrease to less than 0.2 within one month after the prediction starts. Potential predictability studies show that the fraction of variance over land forced by SST is generally modest (for example, Sugi et al.[40]; Peng et al.[41]), and average prediction skill over land is likely to remain fairly low, assuming that current models contain the major sources of predictability

(Section 4.2). These average results are not representative of regions where surface air temperature or precipitation anomalies are created by atmospheric teleconnections from ENSO-related heat sources or other predictable forcing, where skill can be higher.

Probabilistic prediction skills like the Brier Skill Score (BSS) and the Relative Operating Characteristic curve (ROC) score [42] are more appropriate for probabilistic seasonal forecasts than are deterministic scores such as TCC or MSSS, especially for regions with only modest predictability. The ROC is part of the WMO SVS-LRF and is relevant to the potential for using the forecasts in decision-making, but does not include information on the reliability of the model forecasts. The BSS includes the term of reliability as well as that of resolution for probabilistic predictions [43].

The BSSs of the DEMETER MME 1-month lead hindcasts are summarized in Table 1 for upper and lower tercile categories of seasonal mean surface air temperature and precipitation anomalies for June-July-August (JJA) and December-January-February (DJF) during 1980–2001. The skills are strongly dependent on regions and seasons. The forecast quality of surface air temperature is higher than precipitation over most areas regardless of season. Significant skill is indicated for monsoon precipitation anomalies over some tropical regions like DJF Amazon and JJA South-East Asia. Statistically significant skills for surface air temperature extend beyond the tropics to extra-tropical land regions in some cases, including Australia, southern South America, western North America and the Mediterranean Basin in JJA, and Southern Africa and east Asia in DJF.

Table 1. Results from DEMETER

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**
South-East 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	**14.1**	9.1	-1.2	1.8	-1.3	-2.5	-0.7	-2.8

Source: Palmer et al., 2004 [29], as reproduced in Kirtman and Pirani, 2008 [44]

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 $E^{\pm}_{T,P}$ (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 $p \geq 0.9$ that a random sample based on a 10 000 bootstrap re-sampling procedure would yield BSS<0 (significantly negative) or BSS>0 (significantly positive).

The prediction skills obtained from long-term hindcast statistics do not represent all facets of seasonal forecasts. Seasonal predictability varies from year to year: for the large ENSO periods of 1982/1983, 1987/1988 and 1997/1998, the spatial correlation coefficients of the DEMETER MME 1-month lead prediction for JJA precipitation in the tropics increase above the 5 per cent significance level of about 0.4 [29]. Similarly, 1-month lead DEMETER MME forecasts for large ENSO years tend to predict observed DJF anomaly of the PNA index indicating the response of an ENSO-related extra-tropical mode [29].

2. Forecast methods and formats

2.1 Seasonal prediction methods

Seasonal prediction methodologies include prediction tools that could be categorized into two classes: empirical and dynamical, with each having their advantages and disadvantages that are often complementary in nature. Operational seasonal prediction forecasts at many centres generally depend on a blend of information provided by empirical and dynamical prediction tools.

Empirical seasonal prediction methods depend on identifying relationships between different variables based on historical observed data. One such example is the sea-surface temperature variability in the equatorial tropical eastern Pacific associated with the El Niño–Southern Oscillation, and its influence on the global climate. Such relationships, referred to as teleconnection patterns, are obtained by subjecting the observational data record to various statistical analyses, and once established, are used for seasonal predictions. The empirical methods to establish such relationships vary in their level of sophistication, and range from simple linear regression to more complex procedures, for example, Canonical Correlation Analysis (CCA). Van den Dool [45] provides a good overview of empirical seasonal prediction methods.

The advantages of empirical seasonal prediction methods are that their development does not require extensive computing resources, and since the prediction methods depend on the observational data, prediction methods are also unbiased. The empirical prediction tools also have certain disadvantages, for example, empirical methods rely dominantly on linear relationships; are not equipped to predict unprecedented conditions that have not occurred in the historical database (including non-stationarity of climate); and are limited by the length of the observational data.

Dynamical seasonal prediction methods utilize comprehensive general circulation models. Initial prediction efforts depended on the use of the atmospheric general circulation models (AGCMs) and have now evolved to the use of coupled ocean–atmosphere general circulation models (OAGCMs). The prediction method involves the specification of the initial state of the component systems – ocean, atmosphere, etc. – and is followed by the forward integration of the OAGCM that provides the future evolution and prediction of the seasonal mean for relevant variables. To sample the inherent uncertainty of seasonal predictions, model integrations include an ensemble of forecasts from slightly perturbed initial conditions or model formulations.

The advantages and disadvantages of the dynamical prediction methods tend to be complementary to those of the empirical methods. Dynamical methods are well suited to handle unprecedented forecast conditions, particularly the non-stationarity of climate, and are not constrained by linearity (for example, between SSTs and their influence on global climate). Dynamical methods are also well suited to sample the spectrum of possibilities related to various outcomes of seasonal mean states, and use of the ensemble method is a powerful tool for probabilistic seasonal forecasts. On the other hand, dynamical methods require large computing resources and an extensive investment in data assimilation systems, and can also suffer from large model biases and errors in model response to forcing.

Users of seasonal forecasts require relevant information on a local spatial scale, and at a temporal resolution required for the application models (for example, a crop model). Seasonal forecasts, on the other hand, tend to represent large-scale structures, and are often given as seasonal time-means. Their utility for different applications, therefore, requires spatial and temporal downscaling. To date, downscaling techniques have been mostly statistical in nature, and have relied on procedures like weather generators to convert forecasts of seasonal means to information with a higher temporal resolution, although in some cases high frequency data from numerical models are used directly, for example, in the calculation of hurricane statistics. Downscaling can also be achieved by embedding regional models within the global prediction models; however, such methods are computationally expensive, and have yet to demonstrate clear advantages over statistical downscaling.

2.2 Calibrating seasonal forecasts in a changing climate

Real-time seasonal forecasts need to be complemented by an extensive set of retrospective forecasts (often referred to as hindcasts). The need for such hindcasts is manyfold. First, users of seasonal forecasts require an estimate of skill and reliability of the forecast system, and hindcasts are necessary to provide such skill assessments. Second, hindcasts also provide a way to calibrate forecasts against the observations, and remove biases that are often part of the dynamical prediction systems. Different ways of calibrating forecasts have been developed and range from simple procedures such as removal of mean bias to complex methods like Bayesian correction. Hindcasts and associated skill estimates are also required in developing appropriate multi-model consolidation techniques combining forecasts based on several models.

As calibration depends on the comparison of past observations against the corresponding hindcasts, calibration can be a challenging problem in a non-stationary climate, if the hindcast system does not correctly represent relevant processes. For example, early generations of dynamical prediction systems specified fixed CO_2 concentrations, despite the fact that greenhouse gas variations over the hindcast period were considerable. It became apparent that in such systems the forecasts were unable to maintain the correct surface temperature anomalies relative to past dates. Newer generations of hindcast/forecast seasonal prediction systems now include time-evolving concentration for the greenhouse gases and this contributes to seasonal forecast skill.

Recent climate trends, for example, increases in surface temperature, can also be used for seasonal prediction. As the seasonal forecasts are based on a reference climatology, recent trends relative to the reference climatology is a component that is often used to trend-adjust empirical seasonal forecasts [46]. The possibility of adjusting dynamical forecasts needs careful consideration: on the one hand, there may be robust evidence from the hindcasts that the model is not capturing some of the observed changes in climate; on the other hand, it is not always easy to know whether certain aspects of recently observed changes are a trend that will be continued, or some variability that may be more likely to reverse. This is a point at which seasonal prediction has strong interactions with decadal climate prediction and climate change research.

2.3 Communicating forecasts, and interaction with user community

The processes by which seasonal forecast information is disseminated and communicated to the wide range of potential and actual users are in many cases still in need of substantial improvement. This is particularly true in regions and for user groups where resources to access and use the data are limited. Although producers of numerical seasonal forecast data do not have lead responsibility for these issues, they will inevitably have to play a part in ensuring that the right data are produced and made available to those who need them. Robust systems of communication and appropriate levels of resources (including on the producer side) are needed to ensure that seasonal-timescale climate information is properly utilized.

Over approximately the last decade the Regional Climate Outlook Forum (RCOF) has provided a primary mechanism for communicating climate information, predominantly seasonal forecasts, to various user communities [47]. The RCOFs take a variety of formats, but a common element has been the generation of climate information through a consensus-building process. They represent a potentially important conduit for communicating WMO Global Producing Centre (GPC) products to end-user communities. To date, however, the uptake of GPC products by most of the RCOFs remains weak for a variety of reasons. Access to GPC model hindcasts and digital versions of the current forecasts is limited and so it is difficult to know exactly how to incorporate the outputs into a forecast, even subjectively. The establishment of the Lead Centres (LCs) for multi-model ensembles and for verification have addressed these problems to some extent, but the information provided by the LCs remains of only limited value for facilitating the use of the GPC products. Problems include: (a) poor connectivity between the GPC outputs available from the LC for multi-model ensembles and those for verification so the users cannot easily view the verification information for current forecasts; (b) poor levels of compliance in submitting verification results despite this being a requirement of achieving GPC status; and (c) the highly technical nature of much of the information provided. However, improvements to the information provided by the LCs is only a partial solution: further progress in promoting the use of GPC products is probably best achieved by building the capability to downscale (statistically, or possibly in some cases, dynamically) the GPC products at, or in preparation for, the RCOFs.

Simply increasing the consideration given to GPC products is unlikely to address the problem of the currently limited application of seasonal forecasts. The lack of transparent and easily comprehensible verification information on the quality of the forecasts needs to be addressed, but more importantly, the forecasts are difficult to understand, and they do not map on to anticipated impacts very clearly or easily. Translating the forecasts into simpler language can help considerably, and progress has been realized at some RCOFs through writing forecast statements in close collaboration with media experts. Of even greater value would be the tailoring of forecasts to be more directly related to the variables of interest to potential users, and, where possible, the presentation of forecasts into formats that can be used as direct inputs to application models. This tailoring involves the prototyping of products that extend beyond the widespread tercile probability forecasts to generalized probability distributions that are amenable to more problem-specific applications, as well as to predictions of intra-seasonal statistics, and to a more comprehensive provision of climate information beyond seasonal forecasts. For many end-users, seasonal forecasts are only one component of a wide range of climate information products from which they could benefit.

The provision of tailored information lies at the heart of some of the sectoral outlook forums that have developed in recent years. Examples include the malaria outlook forum (MALOF) and food security outlook forum (FSOF). These forums, which have typically taken a sectoral theme, are distinct from the RCOFs. Just as the GPC products will only see wide use at the RCOFs when there is a sense of ownership by the users (the RCOF participants), so the sectoral forums can only be successful when they are owned by the sectoral experts rather than the climatologists.

3. Current capabilities for seasonal prediction

3.1 Internationally coordinated research

Current capabilities for seasonal prediction have grown out of work done in the research community at both national and international levels, as described in this section. The research community is still actively involved in the development of seasonal prediction, and in many cases there are still overlaps between research and real-time forecast production. Ensuring good links between the international organization of research and of operational activities is important for the efficient and effective development of seasonal prediction, and may well be an important issue when considering the Global Framework for Climate Services (GFCS) for longer timescales.

Since its creation in the early 1980s, the World Climate Research Programme (WCRP) has encouraged the use of numerical models (atmosphere-only first, coupled ocean–atmosphere later) to explore the possibility of long-range forecasting. In the 1980s this forecast range meant timescales beyond medium-range (day 5–10), and corresponded to typically day 10–30 [48]. The role of WCRP was to promote dissemination of the latest results in the so-called Working Group on Numerical Experimentation (WGNE) blue book and to organize international workshops in the modelling community to exchange results and methods for forecast production and forecast evaluation. At this stage WCRP did not organize strongly coordinated hindcast experiments. However, in the late 1980s, WCRP with the Programme for Climate Models Diagnosis and Intercomparison (PCMDI) launched the famous Atmospheric Model Intercomparison Project (AMIP) which served as a template for all later common modelling projects [49].

The first coordinated seasonal hindcast experiment appeared in Europe as a European Commission-funded project named PROVOST (PRediction Of climate Variations On Seasonal to interannual Time-scales) [50]. This experiment did not measure the actual forecast skill in the seasonal range because observed rather than predicted SST was used. At that time, the ocean models were not mature enough to be fully coupled over the globe and no proper initial state was available for the ocean. However, the results were of great importance in establishing the potential of numerical models to predict part of the future evolution of the atmosphere. In addition, it was shown that when one model is successful (in 1983 in the Pacific, in 1989 in Europe) the others were also successful. The mean skill in mid-latitudes is weak, but the year-to-year skill is not uniformly low and the higher values of the scores are not distributed at random among the models.

The PROVOST project (1996–1999) was followed by two similar projects. The Dynamic Seasonal Prediction project (DSP) [51] involved five United States modelling groups: the National Center for Atmospheric Research (NCAR), the Center for Ocean–Land–Atmosphere Studies (COLA), the Goddard Space Flight Center (GSFC), the Geophysical Fluid Dynamics Laboratory (GFDL) and the National Centers for Environmental Prediction (NCEP). The Asia Pacific Economic Cooperation (APEC) Climate Network

(APCN) involved partners in the Asia-Pacific region (Australia, Canada, China, Chinese Taipei, Japan, the Republic of Korea, the Russian Federation and the United States). In this project, attempts were made to use predicted SSTs.

The follow-up of PROVOST in Europe was the European Commission-funded DEMETER project (2000–2003) [29]. The main novelties of the DEMETER project were the extension of the number of models (7 coupled models), the forecast range (6 months) and the experiment size (44 years), but mainly the fact that the SST was no longer prescribed from observations but predicted by the coupled models. The estimates of prediction skill for DEMETER were, as expected, less than in PROVOST, but remained positive in some parts of the world, including most of the tropical belt. The DEMETER project also allowed much research on multi-model techniques, and triggered similar activities elsewhere: the continuation of DSP with coupled models in the United States; and the Seasonal Model Intercomparison Project (SMIP), a comparison co-organized by WCRP and the Programme for Climate Models Diagnosis and Intercomparison (PCMDI, one of the series of Model Intercomparison projects after the Atmospheric Model Intercomparison Project). It included PROVOST, DEMETER, DSP and APCN.

A consequence of the research successes with multi-model systems was a push towards operational multi-model systems, such as the European Association for Signal Processing (EURASIP) in Europe, APCC in the Asia-Pacific region and the International Research Institute for Climate and Society (IRI).

Most recently, research in Europe has been coordinated under the European Commission-funded ENSEMBLES project (2004–2009). Unlike earlier projects, ENSEMBLES is primarily devoted to climate change, with seasonal hindcasts as one component of the model assessment. Annual and decadal range forecasts are also part of the project. Alongside ENSEMBLES, a WCRP project named Climate-system Historical Forecast Project (CHFP) has been started. This project aims at extending the ENSEMBLES/US-DEMETER framework to all voluntary modelling groups and at producing a distributed database with a common list of diagnostics with a common format. Although it is led by the Working Group on Seasonal-to-Interannual Prediction (WGSIP, part of the Climate Variability and Predictability [CLIVAR] programme), it involves all parts of WCRP – the Global Energy and Water Cycle Experiment (GEWEX), the Stratospheric Processes and their Role in Climate (SPARC) programme, and the Climate and Cryosphere Project (CliC), and attempts to consider the role of the whole climate system in seasonal prediction. Its database should provide a valuable and freely accessible resource for researchers worldwide, particularly for investigating what levels of skill exist in different regions of the world, and how seasonal forecast model data can best be used.

3.2 National and regional production of seasonal forecasts

Over the last decade or more, a number of national meteorological services and a few other organizations have started to run numerical models for the purposes of seasonal prediction. The Appendix to this paper provides information on some of the forecasting systems available around the world, including both national and regional or international capabilities.

It is this distributed global capacity for seasonal forecasting which provides the basis for WMO to coordinate an internationally organized system for the production, distribution and verification of seasonal forecasts from numerical models.

3.3 International coordination of operational systems

3.3.1 Global Producing Centres for Long-Range Forecasting

The Commission for Basic Systems (CBS), during its thirteenth session in 2005, noted that significant progress had been made over the last decade in long-range forecasting (from 30 days up to two years). The Commission recommended that Global Producing Centres (GPCs) for Long-Range Forecasting (LRF) should be officially designated. That would allow institutions outside the World Weather Watch system with demonstrated capabilities in LRF production and services to be officially recognized as such and to make their products available. In order to be recognized as a GPC, a centre must provide global forecast products during a fixed production cycle, have a minimum set of products (for example, 2m temperatures and precipitation), verification statistics as per the WMO Standardized Verification System, provide up-to-date information on the methodologies used and make forecast products available through its own Website or other specified methods. The requirements are specified in Appendix II-8 (page 68) of the WMO Manual on the Global Data-Processing and Forecasting System [35]. At the time of writing, 11 GPCs are designated by WMO, namely, Beijing, ECMWF, Exeter, Melbourne, Montreal, Moscow, Pretoria, Seoul, Tokyo, Toulouse and Washington, with the Centre for Weather Prediction and Climate Studies (CPTEC) in Brazil likely to be added soon.

3.3.2 Standardized Verification System

The Standardized Verification System for LRF allows forecasting centres to document skill levels measured according to a common standard. The SVS is defined in Attachment II.8 (page 122) of the WMO Manual on the Global Data-Processing and Forecasting System [35]. A Lead Centre for SVS-LRF has also been assigned, with responsibilities which include an associated Website displaying verification information in a consistent and similar way. This is co-hosted by the National Meteorological or Hydrometeorological Services (NMSs) of Australia (Melbourne) and Canada (Montreal). Unfortunately, not all of the designated GPCs have been 100 per cent compliant in submitting verification information to the Lead Centre despite the fact that this is a minimum requirement.

3.3.3 Regional Climate Outlook Forums

Real-time regional forecasts are routinely produced through consensus discussion forums held in various regions globally, the so-called Regional Climate Outlook Forums. The forecasts produced by participating NMSs of the region are a result of consideration of empirically based models developed prior to the forecast meeting, and consideration of forecasts produced by some GPCs. The forums take place in the Greater Horn of Africa, Southern Africa, west Africa, Asia, the western coast of South America, the south-east of South America, the Pacific islands, Central America, south-eastern Europe, and the Caribbean. Issues concerning RCOFs were discussed in Section 2.3.

3.3.4 Lead Centre for Long-Range Forecast Multi-Model Ensembles

The CBS in November 2006, and the fifteenth WMO Congress noted that a number of issues concerning LRF needed to be studied, including a possible role for one or more GPCs to collect global LRF data to build multi-model ensembles. The need for a Lead Centre for LRF Multi-Model Ensembles was subsequently identified, and GPC Seoul (Republic of Korea) and GPC Washington (United States) have been jointly designated by WMO as a Lead Centre for Long-Range Forecast Multi-Model Ensembles prediction (LC-LRFMME) with responsibility for a Web portal of GPC and multi-model ensemble (MME) products.

Provision of a single portal for GPC information addresses current difficulties experienced by users in merging GPC output into a consolidated forecast for their region. Data formats and forecast visualization products have been developed independently at different centres. Consequently GPCs forecasts are currently available in varying digital formats and visualized on GPC Websites using a wide variety of graphical approaches with no consistent contouring intervals or colour shading conventions and no consistent set of geographical domains. This makes intercomparison of forecast signals from different GPCs difficult, and there is evidence that this discourages users from making collective use of GPC output. The datasets provided by GPCs are standardized by LC-LRFMME, which makes them available to users including National Meteorological and Hydrological Services (NMHSs), Regional Climate Centres (RCCs) and RCOFs. Given the anticipated improvements in skill of LRF by using a multi-model ensemble approach, LC-LRFMME should provide a much needed conduit for GPCs information.

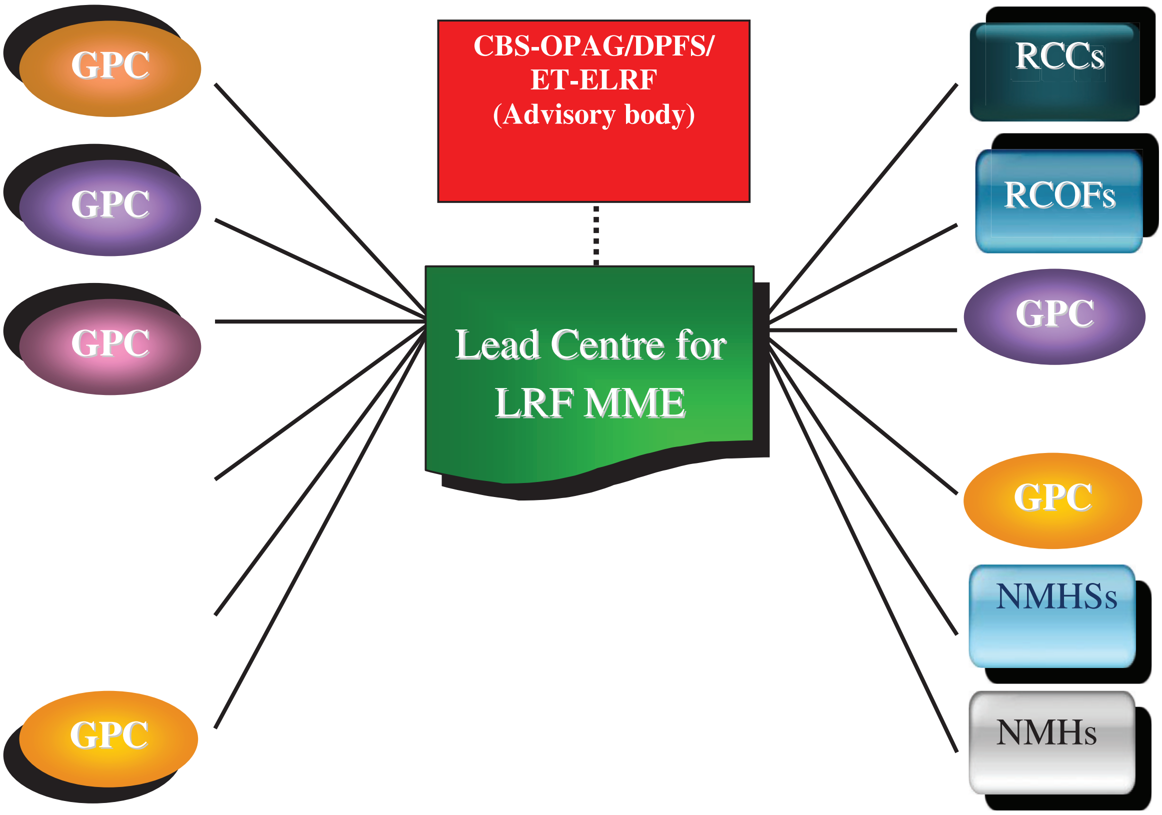

Figure 3. Structure of LC-LRFMME

GPCs are providing an agreed set of data to LC-LRFMME. The provided data are standardized by Lead Centres and disseminated to users through data exchange system of LC-LRFMME.

The LC-LRFMME functions have been developed and refined by the Expert Team on Extended and Long-Range Forecasting (ET-ELRF), and are as follows:

(a) Maintain a repository of documentation for the system configuration of all GPC systems;

(b) Collect an agreed set of forecast data from GPCs;

(c) Display GPC forecasts in standard format;

(d) Promote research and experience in MME techniques and provide guidance and support on MME techniques to GPCs, RCCs and NMHSs;

(e) Based on comparison among different models, provide feedback to GPCs about the models' performance;

(f) Generate an agreed set of Lead Centre products;

(g) Provide Web pages to satisfy requirements for regional display of Lead Centre products (for example, for RCOF coordinators);

(h) Where possible verify the LC products using SVS-LRF;

(i) Redistribute digital forecast data for those GPCs that allow it;

(j) Handle requests for the password for the Website and data distribution; maintain a database recording users who have requested access to data/products and the frequency of access;

(k) Maintain an archive of real-time GPC and MME forecasts.

A Website providing much of the recommended functionality of the LC-LRFMME has been developed (http://www.wmolc.org). The GPC digital products, where authorized by the provider, are available from LC-LRFMME.

Core information consists of monthly mean anomalies for individual ensemble members and ensemble mean for at least each of three months following the month the submissions are provided. Global fields of forecast anomalies supplied by Lead Centres are Surface (2m) temperature, sea-surface temperature, total precipitation rate, mean sea level pressure, 850hPa temperature, and 500hPa geopotential height. Various graphical products, indices, consistency plots, ensemble plumes of Niño indices and energetics are displayed in common format on the LC Website, for the variables listed above and for interactively selectable regions where appropriate.

As part of research and development, the Lead Centre may make available additional products (beyond the core information described above), based on forecast and hindcast data from the subset of GPCs that are able to supply them. These products are additional information to help GPCs, RCCs and NMCs to further develop MME techniques and their application.

Access to GPC data and graphical products from LC-LRFMME Websites will be by password. Recognized GPCs, RCCs, NMHSs and institutions hosting RCOFs such as the African Centre of Meteorological Applications for Development and the Intergovernmental Authority on Development (IGAD) Climate Prediction and Applications Centre are eligible for access to information held and produced by the LC-LRFMME.

The GPC Seoul and GPC Washington LC-LRFMME is now fully functional, makes GPC forecast products available to users and has already entertained requests from the RCOFs.

4. Requirements for seasonal prediction

4.1 Initial conditions

Dynamical seasonal prediction is essentially an initial value problem, where predictive skill comes from information contained in the initial states of the coupled system. Most of the skill comes from the initial conditions of the upper ocean, particularly those associated with large-scale patterns of variability such as ENSO and the Indian Ocean dipole.

Assimilation of ocean observations for ocean initialization in seasonal forecasts has become a common practice, with several institutions around the world producing routine ocean reanalyses to initialize their operational seasonal forecasts. Table 2 provides a summary of the ocean analyses used for initialization of operational or quasi-operational seasonal forecast systems. In all these systems, the initialization of the ocean and atmosphere is done separately, aiming at generating the best analyses of the atmosphere and ocean through comprehensive data assimilation schemes in both media, although there are emerging attempts at approaching the initialization as a coupled ocean–atmosphere problem.

For ocean initialization the emphasis is on the initialization of the upper ocean thermal structure, particularly in the tropics, where observational information about SST is essential. High quality wind stress forcing is needed, since this largely determines the gradients of sub-surface structure. Wind stress often comes from NWP-based atmosphere data assimilation systems, but these depend on the input data, including Tropical Atmosphere Ocean (TAO)-type moorings and space-borne scatterometry. Most of the initialization systems also use subsurface temperature (from expendable bathythermographs, TAO/TRITON/PIRATA (Prediction and Research Moored Array in the Tropical Atlantic) and Argo), most recently also salinity (mainly from Argo) and altimeter derived sea-level anomalies (SLA). The latter usually needs the prescription of an external Mean Dynamic Topography (MDT), which can be derived indirectly from gravity missions such as the Gravity Recovery and Climate Experiment and, in the near future, the Gravity Field and Steady-State Ocean Circulation Explorer. The resulting ocean reanalyses are a valuable data resource for climate variability studies and have the advantage of being continuously brought up to real time. They are being used experimentally for the initialization of decadal forecasts.

Several studies have demonstrated the benefit of assimilating ocean data on the prediction of ENSO [59][60][61]. The benefits are less clear in other areas, such as the equatorial Atlantic, where model errors are large. Balmaseda and Anderson [62] evaluate three different initialization strategies, each of which uses different observational information. They show that the ocean initialization has a significant impact on the mean state, variability and skill of coupled forecasts at the seasonal timescale. They also show that, using their model, the initialization strategy that makes the most comprehensive use of the available observations leads to the best skill.

The importance of salinity observations is discussed in Fujii et al. [63]. The results of Usui et al. [52] indicate that only when salinity observations are assimilated is it possible to represent the strong meridional salinity gradient in the western equatorial Pacific, with low salinity waters north of the equator. Results also show that without the balance relationship between temperature and salinity it is not possible to represent the high salinity of the South Pacific tropical water, leading to the erosion of the vertical stratification and eventual degradation of the barrier layer.

Table 2. Summary of different ocean assimilation systems used in the initialization of operational and quasi-operational seasonal forecasts

MRI-JMA http://ds.data.jma.go.jp/tcc/tcc/products/elnino/index.html MOVE/MRI.COM-G. Multivariate 3DVAR. Usui et al.[52]
ORA-S3 (ECMWF System 3) http://www.ecmwf.int/products/forecasts/d/charts/ocean/real_time/ HOPE/OI: Multivariate OI. Balmaseda et al.[53].
POAMA – PEODAS (CAWCR, Melbourne) http://poama.bom.gov.au/research/assim/index.htm Multivariate Ensemble OI. Alves and Robert [54]
GODAS (NCEP) http://www.cpc.ncep.noaa.gov/products/GODAS/ MOMv3/3Dvar. Behringer [55]
MERCATOR (Meteo France) http://bulletin.mercator-ocean.fr/html/welcome_en.jsp PSYS2G. Multivariate reduced order Kalman filter. Pham et al. [56]
MO (MetOffice) http://www.metoffice.gov.uk/research/ Glosea3. Multivariate OI. Martin et al.[57]
GMAO ODAS-1 http://gmao.gsfc.nasa.gov/research/oceanassim/ODA_vis.php GMAO Seasonal Forecasts: http://gmao.gsfc.nasa.gov/cgi-bin/products/climateforecasts/index.cgi ODAS-1 : OI and EnKF. Keppenne et al.[58]

The seasonal forecast skill can also be used to evaluate the ocean observing system. Fujii et al. [64] evaluate the impact of the TAO/TRITON array and Argo float data on the Japan Meteorological Agency (JMA) seasonal forecasting system by conducting data retention experiments. Their results show that TAO/TRITON data improves the forecast of SST in the eastern equatorial Pacific (NINO3, NINO4), and that Argo floats are essential observations for the prediction of the SST in tropical Pacific and Indian Oceans. Similar results have been obtained with the ECMWF seasonal forecasting system [65].

A new generation of initialization systems is being developed, where the oceanic and atmospheric initial conditions are generated simultaneously using a coupled model and so have the potential of retaining the balances relevant for the coupled system [66][67]. This approach can also be used to include land and sea ice, and thus provide a balanced initial state for the whole coupled system. Coupled data assimilation, while technically and computationally challenging, is likely to provide the best approach for exploiting most of the information from the diverse observing networks, while at the same time maintaining the dynamical consistency required by the models.

Over the last decade there have been significant enhancements to the ocean observing network, namely the Tropical Ocean and Global Atmosphere Programme (TOGA)-TAO array and the altimeter data in the 1990s and Argo this decade. Each of these new observing systems has been demonstrated to benefit the initialization of climate models, with little if any redundancy. The evaluation of ocean analyses does require redundancy and the availability of independent data to assess the analyses. We have not reached that point yet. Further enhancement of the ocean observing system will be needed to improve our ocean state estimates, and to provide independent evaluation of those estimates.

Soil moisture is also an important memory component of the climate system (for example, Koster and Suarez [68]; Seneviratne et al. [21].) and thus a useful source of skill for seasonal forecasting, particularly of near-surface temperature (for example, Koster et al.[69]; Ferranti and Viterbo, [70]). Soil moisture analyses, and the observational data that help support them, are particularly important in shorter-range seasonal forecasts, for example, the first three months. Information contained in the atmospheric initial conditions is particularly important for shorter intra-seasonal timescales, but information contained in the large-scale atmospheric circulation has also been shown to be important for processes such as ENSO [71], reflecting the fact that ENSO is a coupled mode of variability.

In summary, seasonal forecasting has strong requirements both for observational data and for improved data assimilation systems needed to prepare high quality initial conditions. Analyses are needed not only for real-time forecasts, but also stretching back in time (reanalyses) to allow the hindcasts needed for calibrating the real-time forecasts. Reanalyses of ocean, land and atmosphere are all required.

4.2 High quality models of the ocean-atmosphere-land system

Present day seasonal forecast systems, while having significant and useful levels of skill in many cases, are still a long way from delivering forecasts that approach the limits of predictability. This is clear from the published literature (for example, Wang et al.,[30]; Palmer et al.[29]), the experience of modelling groups and the assessment given by the recent WCRP Workshop on Seasonal Prediction [72].

Analysis of ENSO SST forecasts in coupled models suggests that although uncertainty in initial conditions leads to some uncertainty (and hence error) in the SST forecasts, a major part of the forecast error is due to inaccuracies in the models themselves [73]. The exact decomposition of ENSO forecast error between forecast model error and initial condition error remains unknown, but initial condition error may also have a substantial contribution from model error in the ocean data assimilation process [53].

Even when SST is specified, ensembles of atmospheric GCMs do not always reproduce observed seasonal variations in regional climate with the accuracy that should be possible [74]. Indeed, when it comes down to quantitative detail, today's coupled GCMs do not accurately reproduce regional mean climates either. It is thus unsurprising that the seasonal forecast skill of today's systems are substantially below the estimated predictability limits, and probabilistic forecasts from models have relatively poor reliability. The results of perfect predictability studies with current models may also be inaccurate.

Seasonal forecast models, as well as requiring very accurate modelling of basic features of the climate system such as atmospheric boundary layers, convection, land surface processes and ocean mixing, are likely to require adequate treatment of a range of other processes to maximize their forecast skill. For example, aerosol properties, stratospheric forcings and processes and the cryosphere are all likely to need better treatment than they are presently given in seasonal forecast models.

Note that regional climate models, although they can be of some use in downscaling large-scale signals to a more local level, are not the answer to the problem of inadequate global models. If the large-scale forcing is wrong, a regional model will not help.

For the ocean, better models will allow more successful data assimilation and thus enable improved initial conditions to be created from the data we already have.

One way of trying to mitigate the problem of model error is the multi-model ensemble approach, where forecasts from a number of different models are averaged together, or otherwise combined, with the intention both of averaging out some of the individual model errors and also of sampling them, to get a better idea of the likely uncertainty in the composite forecast. The advantages of the multi-model approach have been clearly demonstrated [29][30], and multi-model approaches are now commonplace in operational settings, as described in the Appendix and Section 3. Multi-model studies can also be of use in diagnostic studies, helping clarify cases in which a given model behaves poorly. Ideally, it should be possible to evaluate which models do best in which situations, so as to be able to construct an optimal situation-dependent ensemble forecast. However, the limited number of past cases often limits the effectiveness of such an approach, and simple combinations of models often work just as well, if not better.

Multi-model ensembles have fundamental limitations. Models often have common errors, so a multi-model ensemble neither converges on the truth nor properly samples the uncertainty. Further, if all the models are missing certain sources of predictability, model averaging will not help. The multi-model technique is beneficial, in that it is a straightforward way to improve the forecasts that can be produced using today's models. It is, however, no substitute for improving the forecast models.

It must be recognized that while model improvements are vital, they will not be easy. There exists a substantial scientific base (field studies and in situ data, satellite data, process models) relevant for much of what is needed, but current capacities to integrate this knowledge and produce radically improved predictive models are limited.

The urgent need to improve climate models in general has been recognized by the Joint Scientific Committee of the WCRP, who discussed the issue at their twenty-eighth meeting in 2007, following a report from the WCRP Modelling Panel. This led to the organizing of the World Modelling Summit for Climate Prediction, which took place in 2008, and resulted in both a report and a summit statement [75]. The summit concluded that the societal need for a revolution in climate modelling is evident, and the existing science base is an adequate starting point; that the proposed global climate research facility should focus on the scientific and technical development of advanced models and techniques, while leaving operational prediction to national centres; and that high-resolution global climate models are feasible with the right investment. There was unanimity that current predictions are not adequate, and general agreement that improved information at the regional and local level will require significantly better model resolution and computer resources.

The summit statement calls for a "Climate Prediction Project", involving both enhanced capacity of existing weather and climate research centres, and the creation of a world climate research facility that would include one or more dedicated high-end computing centres.

The seasonal forecasting community does not have the expertise to judge the best strategies for model improvement, and the model resolutions and computer resources that will be required. However, based on the experience of model errors in seasonal forecasting, we do strongly endorse the need for substantial and sustained resources to be made available for model development and improvement. There is no reason to suppose that the model failings that cause problems with regional climate forecasts on seasonal timescales will not also cause problems on longer timescales.

Ultimately, the value of the Global Framework for Climate Services will depend on the quality of the information that can be made available, and this is critically dependent on the ability of our global models to properly handle regional fluctuations in climate. For the sake of both seasonal and longer-term climate predictions, it is thus imperative that models are improved.

4.3 Data for verification and calibration

Observational data are needed not only to initialize seasonal forecasts, but also for model validation and development, and for the purposes of verifying and calibrating the seasonal forecasts themselves. There is thus a need to interact with the data analysis community to improve key datasets for seasonal forecasting, and particularly to create reliable error estimates. This is another area where a synergy exists between seasonal forecasting and climate change.

When it comes to assessing the quality of seasonal forecast systems, access to appropriate verification data is important, both for modelling centres and end-users. The most critical fields for users are 2m temperature and rainfall. One choice is to use reanalysis data, but the appropriateness of using this as "truth" for interannual variability is unclear, particularly for precipitation, which is sensitive to both model physics and the changing makeup of the observing system in present day reanalysis products. In principle, in situ data, either directly or via products such as those from the Global Precipitation Climatology Project, are preferable. However, the availability of in situ data is often limited, and the resulting precipitation analyses have large error bars, which can hamper the assessment of models and forecasts.

For users, downscaling and calibrating the output of global models to produce local values requires good records of local temperature and precipitation. Access to such data, and continuation of the measurement programs that provide them, is important in maximizing the potential value of seasonal forecast systems.

5. Wider context of seasonal prediction and "seamless forecasting"

5.1 Linkages of seasonal prediction to shorter timescales

Seamless prediction is the concept of using common forecasting systems to predict multiple timescales, in particular extending numerical weather prediction (NWP) towards climate timescales. How far and in what form such concepts will eventually be applied in an operational context is unclear, although the scientific benefits of assessing models across multiple timescales are intuitive, and there is much scope for fertile interactions at each of the overlaps in the chain of NWP, extended range, seasonal, decadal and longer-term climate change. Brunet et al. [76] put the scientific case for pursuing seamless prediction.

One issue already being addressed at some operational centres is to effectively extend weather forecasts out to 14 days and beyond, for example, up to 4-5 weeks to fill the gap between weather forecasts and monthly and seasonal prediction. Recent research suggests, if the influence of tropical heating is properly taken into account, weekly averages of extra-tropical weather might be predictable as far as six weeks ahead with comparable skill. Numerous observational studies have shown that the intra-seasonal timescale, with the Madden-Julian Oscillation (MJO) being the most dominant mode, has a comparable timescale (for example, Ding, [77]). The MJO is well documented to be excited by convective heating in the near-equatorial region.

The MJO is a naturally occurring component of the coupled ocean–atmospheric. It can affect the generation, development and movement of tropical storms and hurricanes, and often affects the extra-tropical circulation including Aleutian lows, lower level circulation in the western Pacific, subtropical jet, synoptic-scale disturbances and storm tracks. During late 2007 the United States climate variability and predictability MJO working group began outlining a strategy to develop a uniform metric for real-time dynamic MJO forecast. The Wheeler and Hendon [78] MJO identification methodology has been applied to dynamical model data or statistical/empirical model outputs to predict the genesis of tropical storms, monsoon activity (onset/end, breaks and intensity) and regional rainfall patterns in subtropics and at mid-latitudes. Preliminary experimental prediction at these operational centres for 2007–2008 indicates encouraging skills, especially in the Asian-Australian monsoon region and for the coupled ensemble forecast system.

Although the extended range prediction of intra-seasonal variability has recently emerged as potentially highly useful, there are still some important problems to be solved, including: (a) when the signal of the MJO is very weak, its interaction with subtropics or extra-tropics could not be established; (b) the mechanism of northward propagation of the MJO; (c) underestimating of amplitudes of the MJO generated by most of coupled models used in major operational centres; and (d) impacts from mid-latitudes and their processes of interaction with the MJO.

Started by WMO in 2005, THORPEX (THe Observing system Research and Predictability Experiment) is an international research program that will accelerate improvements in the accuracy of 1-day to 2-week high-impact weather forecasts. However, it will also address the influence of interannual to intra-seasonal atmospheric and oceanic variability on high-impact forecasts out to two weeks, and therefore aspires to bridge the middle ground between medium-range weather forecasting and climate prediction. The key dynamic and physical processes influencing forecast skill out to two weeks are as follows:

(a) Rossby wave excitation and subsequent propagation, and the influence of Rossby wave trains (for example, zonal or blocking states) on the climatology of forecast skill. This regime-dependent forecast skill is strongly related to forecast error of the ISV and interannual variability (for example, MJO, ENSO, NAO and Arctic Oscillation). This evaluation will help improve the skill of EPS forecasts which are modulated by temporal/spatial variations in flow regions. Further improvements in forecast systems will be required to achieve comparable skill out to 14 days and beyond.

(b) In particular, this improvement will focus on improved prediction of initiation and evolution of tropical convection and heating which requires:

(1) Very high model resolution to explicitly resolve convection or alternately improved convective parameterization;

(2) A coupled atmosphere–ocean prediction system with inclusion of three-dimensional evolution of the ocean state;

(3) Improved representation of atmospheric and oceanic boundary layers;

(4) Improved data assimilation and ensemble prediction techniques.

The above is one important example of a link between seasonal prediction and the improvement of forecasting at shorter timescales. Indeed, THORPEX and WCRP are already collaborating on projects to improve models (for example, the Year of Tropical Convection in 2008–2009, and joint submissions to GEO in 2007). More generally, the importance of linkages across timescales has been recognized by the WMO Executive Council, who formed a Task Team on the research aspects of an enhanced climate, weather, water and environmental prediction framework. The Task Team, in its report to the sixty-first Executive Council in June 2009, makes a number of specific recommendations to help accelerate the development of prediction systems. These include a unified approach to multidisciplinary weather, climate and environmental prediction research, investment in enhanced computer resources and accelerated development of prediction models.

5.2 Linkages of seasonal prediction to longer timescales

Recent pioneering work has produced initialized climate predictions out to decadal lead times [79][80]. On this timescale it is not only important to include the initial state of the atmosphere and ocean in forecasts but also to include changes in radiative climate forcings such as greenhouse gases. While these predictions are still at a relatively early stage in their development, they have been shown to generate skilful forecasts of global mean temperature and represent a clear improvement over uninitialized forecasts.

Further tests of the growing number of interannual to decadal forecasts against observations are now required on regional geographical areas to establish levels of regional decadal forecast skill. It is not yet clear how much regional skill is present, but early indications suggest that significant forecast skill exists, not least because of emerging anthropogenic climate change signals. Some additional predictability comes from the major modes of climate variability but again this is not yet well quantified. Testing interannual to decadal forecasts against observations is hindered by the relatively small number of independent hindcast cases in the observational record. Nevertheless, many centres are now focusing on developing initialized decadal predictions and these will form a key contribution to the Fifth Intergovernmental Panel on Climate Change (IPCC) Assessment Report.

Some potential sources of predictability such as decadal variability in solar output (for example, Matthes et al. [81]) or the extra-tropical response to volcanic eruptions [3] may be poorly represented in current interannual forecasts. Further factors such as the Quasi-Biennial Oscillation are often completely absent in models [82] and decay with lead time in forecasts even if initialized correctly [27]. These missing sources of predictability mean that the levels of forecast skill that have been identified so far in prediction and predictability experiments are likely to be underestimates of what will be attained after further model development.

It is likely that a major source of error in current interannual to decadal predictions is introduced from the underlying climate models. Models therefore need to be tested for correct handling of regional climate variability in response to factors such as ENSO and for predictability of decadal climate variations such as the Pacific Decadal Oscillation [83] and the Atlantic Multidecadal Oscillation [84]. Although decadal predictions themselves can only be tested against a limited number of actual cases, the models used can have many relevant aspects of their performance tested by seasonal forecasts. In particular, the physics and dynamics that give rise to the seasonal cycle and interannual variability have a large impact on the mean drift and skill of seasonal forecasts. Seasonal forecasting from realistic initial conditions does not assess long-term drift in the model climate, or the impact of such drift on the model variability, but it does assess the accuracy of model behaviour on seasonal timescales when starting from a realistic mean state. This is true for climate models in general: seasonal forecasting allows rigorous testing of coupled models against observed data in an initial-condition controlled setting [85].

The linkages between seasonal and longer-term climate prediction go beyond tests of a model's seasonal cycle and natural variability. Hindcasts from seasonal forecast systems extend across decades, and proper calibration of seasonal forecasts requires that the hindcasts reproduce appropriately the observed trends during the hindcast period. This turns out not to be trivial, and is one way to partially test a model's ability to handle longer-term changes in climate. Equally, the fact that seasonal forecasts can be sensitive to processes that are more usually considered in longer-term climate change means that the seasonal forecasting community has much to learn from the climate modelling community. A further interesting question is as to whether the patterns of seasonal-to-interannual variability, most notably ENSO, might change in response to a changing climate. Attention is presently focussed on "Modoki" El Niño events, the frequency of which is indicated by some models to increase in a warmer climate [86], and the impacts of which have important differences from the traditional El Niño event centred on the eastern Pacific [87].

On the adaptation side, there are also links between seasonal and longer-term climate prediction. There is a growing requirement for climate predictions on seasonal to decadal timescales. This is being driven by two factors: the first is an increasing risk of climate extremes such as droughts, floods and heatwaves due to anthropogenic change; the second is the fact that many potential users have a planning horizon of seasons to a decade. However, on these timescales only probabilistic forecasts of climate and the risk of extremes can be given. Wide experience of generating, communicating and applying probabilistic forecasts on seasonal timescales now exists, and this can provide a strong basis on which to build probabilistic forecast and application systems for decadal forecasts.

6. Summary, conclusions and recommendations

Seasonal prediction is based on changes in the probability of weather statistics due to changes in slowly varying forcings such as sea-surface temperature anomalies, most notably those associated with El Niño–Southern Oscillation (ENSO). However, seasonal weather can be perturbed by many factors, and is very much influenced by internal variability of the atmosphere, so comprehensive models are needed to identify what can be predicted.

Dynamical seasonal prediction systems are operational or quasi-operational at a number of forecasting centres around the world.

The World Meteorological Organization (WMO) infrastructure for the generation, distribution and verification of seasonal forecasts exists and further enhancements are being implemented.

Seasonal predictability and the achieved level of skill vary spatially and are regime-dependent. For example, predictability is highest in the tropical latitudes, and also during ENSO events. Not all sources of potential predictability are properly understood. Even low levels of skill are perceived to be useful by some users.

Forecast systems are still a long way from reaching their potential.

Model error is still a critical problem. Just because a forecast is produced does not mean that it is right, even in a probabilistic sense. A key lesson from seasonal prediction is that model error is a big contributor to forecast error.

Regional models can be of some assistance in downscaling, but they are not a solution to the problem of errors in global models.

Data for initialization and verification are vitally important, as are the data assimilation systems and reanalyses that make use of them.

Current efforts to extend weather forecasts to 14 days and beyond are an important step to the development of shared models between numerical weather prediction (NWP) and seasonal prediction.

Longer timescale climate variations and seasonal forecasting, although different problems, may share some connected processes and methodologies, and both need high quality models to maximize their reliability. Seasonal forecasting is a relevant test bed for climate models used for near-term climate prediction.

6.1 Recommendations

The quality of information is critically dependent on the quality of models. Although these cannot be transformed overnight, long-term commitment of substantial resources to model and assimilation system development will pay dividends in the future, in terms of improved climate information at all timescales. Provision of computer resources to allow development of extremely high-resolution global modelling should be pursued.

The progress of relevant observing systems, including many of the ocean and land components of the Global Climate Observing System (GCOS), is crucial for improving seasonal prediction. The maintenance and improvement of observing systems, data assimilation systems and reanalyses must all be supported.

Access to both observational and forecast data should be widely possible and easy.

Any development of infrastructure for the Global Framework for Climate Services should take account of the work already coordinated by WMO for seasonal forecasts.

Distributing seasonal or other climate forecast data is not enough. Care and resources should be given to producing estimates of forecast quality, including appropriate allowance for model error.

Where possible, developing and testing models and forecast systems across a range of timescales is good practice. Developing a good global capacity for seasonal prediction has high value in itself, but may also help strengthen capacity for climate information on longer timescales.

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Appendix: Regional capabilities for numerical Seasonal Forecasting

We present a summary of numerical seasonal prediction capacity around the world, detailed on a regional and national basis. This is not an exhaustive list, but contains details both of many of the GPCs and also of other international organizations involved in the production of seasonal forecasts, some of which are outside the WMO framework. The list is ordered according to WMO regions.

Africa

South Africa

The South African Weather Service (SAWS) operates a NEC SX-8 machine that hosts the ECHAM4.5 AGCM. The SAWS has recently been awarded GPC status. The ECHAM4.5 forecasts forms part of the SAWS's multi-model forecasting system that produces 3-month seasonal rainfall and temperature (minimum and maximum) probabilistic forecasts up to five months ahead for the Southern Africa Development Community (SADC). Additional GCMs currently feeding into this multi-model system include the CFS (NCEP), the CCM3.6 (administered by the IRI) and the CCAM (forecasts produced at the University of Pretoria). Forecasts with the multi-model also include probabilistic estimates of the streamflow within 1946 quaternary catchments across South Africa. In addition to these forecasts, the SAWS also produces SST forecast products, which include probabilistic forecasts for ENSO, the south-western Indian Ocean SST, Benguela Niño events, and global SST anomalies. For the SST multi-model forecasts, forecasts obtained from the IRI produced by the ECHAM4.5-MOM3 coupled model are also included.

The Universities of Cape Town and Pretoria also run global models for LRF timescales. The models include the HadAM3 and Conformal-Cubic Atmospheric Model (CCAM), both forced with persisted SST anomalies. These forecasts are routinely displayed on the Global Forecasting Centre for Southern Africa (GFCSA) website (www.gfcsa.net).

Asia

China

The official issue of monthly and seasonal prediction was made by China Meteorological Administration (CMA) in 1950s by using various statistical methods. Since the establishment of the National Climate Center (NCC) of CMA in 1995, the coupled climate model was developed by joint efforts of CMA and Institute of Atmospheric Physics of Chinese Academy of Sciences, and then has been used in operational monthly and seasonal prediction (CGCM 1.0/BCC). For ensemble prediction (48 member) of flooding season (JJA), with lead time of 3-month (starting from February), the predictive skill (ACC) of the CGCM is very close to the official prediction issued by NCC by using multi-models (13 dynamical and statistical models) (Figure A1). It shows that dynamical prediction play a more and more important role in operational seasonal prediction. Figure A2 shows a comparison of the skills of official monthly prediction and monthly dynamic prediction of surface air temperature for 1982-2008 (dynamic hindcasts for 1982-2002). It can be seen that the skills of monthly dynamic prediction with different lead time are on the average significantly higher than officially-issued predictions. It is very interesting to note that since 1990s the latter is much closer to the former, implying that the climate forecasters more and more use products of dynamic prediction in formulating their officially issued prediction. In the near future the second generation of coupled climate model with improved parameterization schemes and the assimilation method will put into operational use, which is expected to improve the predictive accuracy of multi-models ensemble monthly-and seasonal prediction based on dynamic and statistical models.

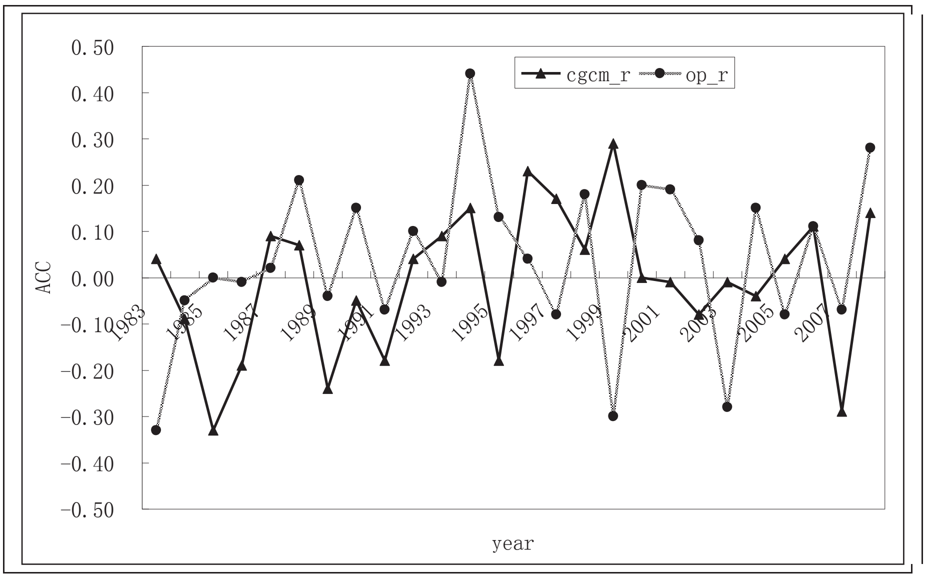

Figure A1. Seasonal prediction skill (ACC) of precipitation in flooding season (JJA) starting end of February by using coupled ocean-atmosphere climate model. The official prediction is shown with solid lines with black dots.

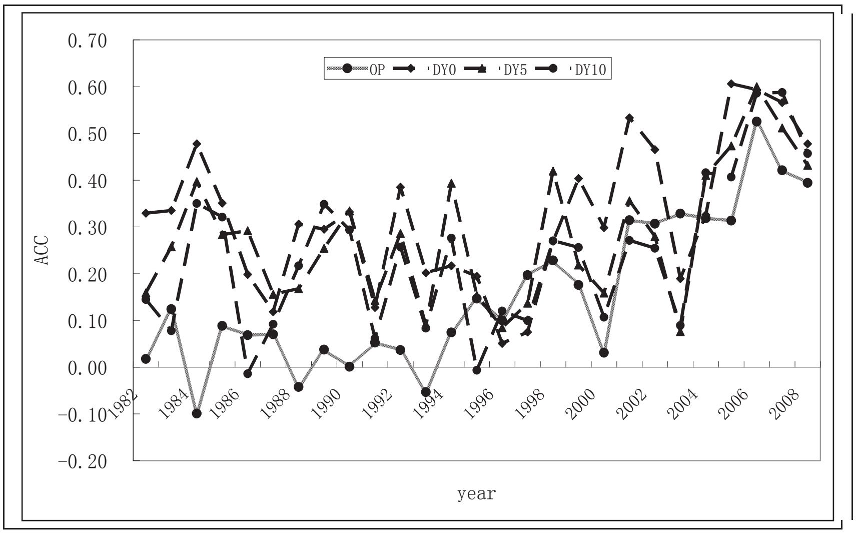

Figure A2. Skills (ACC) of monthly dynamic prediction for temperature with different lead times (0, 5 and 10 days). The officially-issued prediction is indicated with solid lines with black dots.

Japan

Japan Meteorological Agency (JMA) has conducted operational 1-month and 3-month lead forecasts for seasonal and monthly mean surface air temperature, precipitation and other fields in a two-tier way with a 180km version of JMA Global Spectral Model (JMA-GSM) and independently predicted SST anomaly from the JMA coupled prediction model for El Niño. The worldwide products from seasonal forecasts are provided from Tokyo Climate Centre as one of the WMO GPCs. Within the fiscal 2009 year, the JMA/Meteorological Research Institute (MRI) coupled model (JMA/MRI-CGCM) will be employed for all the JMA long-range forecasts. The 3-month lead forecast for JJA surface air temperature anomaly over Japan is expected to be much improved as well as the Asian summer monsoon-related precipitation and SST anomalies [88].

Experimental seasonal prediction studies are performed in the Japan Agency for Marine-Earth Science and Technology JAMSTEC). Their coupled model, SINTEX-F, produces highest-level skill predictions for Niňo3.4 SST anomaly (Luo et al. 2008) and is also used for studying the Indian Ocean Dipole predictability [89].

Korea

The Korea Meteorological Administration (KMA) produces three types of long-range forecasts: 1-month and 3-month forecasts, and seasonal climate outlook. The 1-month forecast is issued three times a month and includes a 10-day mean temperature and precipitation, and a characteristic pressure pattern for each 10-day period. The 3-month forecast which is produced on a monthly basis, includes a monthly temperature and precipitation, and a characteristic pressure pattern for each month. This forecast also includes special seasonal event outlooks such as Asian dust outlook for spring and Typhoon outlook for summer and autumn. The seasonal climate outlook is issued four times a year: February for the summer climate outlook; May for the autumn climate outlook; August for the winter climate outlook; and November for the spring climate outlook. The KMA operates the Global Data Assimilation and Prediction System, called GDAPS, for long-range forecasts. The GDAPS uses predicted SST provided by SST prediction system. In order to support the operational LRF, especially for local provinces, a dynamical downscaling system has been constructed by the National Institute of Meteorological Research (NIMR). The development of a 12-month climate prediction system is under way.

APEC Climate Center

The APEC Climate Center (APCC), based on the APEC Climate Network, produces every month real-time operational climate predictions over the next three months, based on a well-validated multi-model multi-institute ensemble (MME) system. Model simulations from 15 prominent climate forecasting centers and institutes in the APEC region are collected and combined using state-of-the-art schemes to produce a statistically 'consensual' forecast. Because of the way the statistical results are interpreted and verified based on the past performance of the MME, the ensemble forecasts, in general, give a more reliable forecast than the individual models involved. In particular, the MME methods have been successful to the extent of forecasting the atmospheric circulation processes as well as the general global patterns of temperature and rainfall. However, when it comes to the station level prediction, the performance is still not always accurate.

To improve the predictions at station level, APCC has, since last 2-3 years, started development of statistical regionalization techniques, called as 'downscaling' in technical terms. This technique is feasible thanks to the ability of individual models to reasonably predict large scale circulation features associated with regional rainfall/temperature. For any given station, an empirical mapping from the large scale fields to the station level predictand is established based on retrospective forecasts for the past years. Once established, the technique allows for a more reliable station level prediction of rainfall and temperature from the large scale MME forecasts.

To facilitate and encourage better utilisation of climate information, APCC also maintains an open data policy and serves digital real time climate forecast and also hindcast data through its data service. In addition, the newly initiated Climate Information Tool

Kit (CLIK) provides climate researchers and users a convenient way to customise climate forecasts using advanced web-based technologies.

As of now, APCC also carries out climate monitoring. Among its other future projects, APCC is developing a 6-12 month prediction based on a MME of coupled ocean-atmospheric models, important because of the role of the tropical oceans on these timescales. This system is expected to be operational in next year or so. Also planned are operational predictions of drought and other extreme events. Thanks to collaboration under the umbrella of APEC, APCC contributes to the prosperity of the community through successful prediction of climate, and other information services.

South America

Brazil

The Center for Weather Prediction and Climate Studies – CPTEC in Brazil runs its seasonal forecast system based on both a two-tier Atmospheric General Circulation Model (CPTEC's AGCM) at resolution T062L28 forced by prescribed global SST fields and a one-tier AGCM fully coupled to GFDL’s MOM3 ocean GCM (CGCM) over the global tropics, with ¼ degree lat-lon resolution between 10S and 10N over the Atlantic, spacing to 2.75 at 40 degrees South and North and over the Indian and Pacific Oceans. The CGCM uses persisted SSTA poleward of 40 degrees latitude. The two tier system is run for four AGCM physics configurations, 15 members each, for both persisted SST anomalies and SST forecasts from NCEP's CFS for the tropical Pacific and CPTEC's cannonical correlation method for the tropical Atlantic. These runs are used to create CPTEC’s monthly 120 member multi-model ensemble global seasonal rainfall and temperature predictions up to one season ahead. The seasonal forecast skill is measured by anomaly correlations of precipitation and temperature from a 10 member 50 year long retrospective runs for the AGCM [90] and 20 year runs for the CGCM. Also, a 15 members extended-range weather forecast up to 15-day AGCM and 2 members CGCM (both at atmospheric resolution T126L28) for up to 35-day are done daily. The objective ensemble seasonal predictions are discussed by experts during monthly seasonal forecast fora, in which climatologists and users from the whole country participate remotely in real time (using graphic software Visitview®) via the internet. The continental-scale seasonal forecast generated during the national discussion is then downscaled by state bureaus of meteorology and water resources using statistical and dynamical techniques. The seasonal climate forecast fora have been in place for more than a decade in Brazil, and have proved to be an effective way to ensure the desired capillarity of the climate information dissemination.

A new version of CPTEC CGCM being tested uses MOM4's FSM coupler to couple the MPI version of CPTEC AGCM at resolution T213L64 to MOM4 globally with resolution 1 degree longitude and ¼ degrees latitude in the deep tropics relaxing to 1 degree at 40N-S and poleward, with 40 levels in the vertical. The model incorporates sea ice and marine biogeochemical modules.

North and Central America

Canada

Environment Canada (EC) has been producing fully objective model-based seasonal forecasts of surface air temperature and precipitation anomalies for Canada, produced at the Canadian Meteorological Centre (CMC), since September 1995. Operational seasonal predictions are available at http://www.weatheroffice.gc.ca/saisons/index_e.html in the form of deterministic and probabilistic 3-category forecasts for rolling 3-month seasons.

At present these are two-tier forecasts where persisted SST anomalies provide the boundary conditions for 10-member ensembles of forecasts made with each of four AGCMs resulting in a 40-member multi-model ensemble. GCM2 and GCM3 [91][92][93] are second and third generation atmospheric general circulation models from the Canadian Centre for Climate Modelling and Analysis (CCCma) while SEF and GEM-CLIM (Ritchie [94]), are based on two generations of atmospheric forecast models from Recherche en Prévision Numérique (RPN)).

Each forecast is accompanied by an indication of historical skill based on results from HFP2, the second Historical Forecasting Project [95], which follows an earlier HFP1 project [96]. Figure C1 gives the correlation skill for temperature over Canada for the four main seasons. HFP-based studies include analyses of forecast skill and sensitivity together with methods of combination, calibration and post-processing of forecasts (for example, Kharin et al. [97]; Kharin and Zwiers, [98][99]; Boer, [6][100]).

Multi-season one-tier coupled seasonal forecasts are being actively developed and the results of the first Coupled model Historical Forecasting Project (CHFP1) are described in Merryfield et al. [101] and provide a basis against which to compare improvements in the coupled forecast system before implementation. CHFP1 forecasts are initialized by relaxing the coupled system to observation-based SSTs and then releasing the system to evolve into the future. While this simple approach works well, gains of skill are expected in CHFP2 which uses improved model components and initializes both atmosphere and ocean based on observational information. The intention is to use CHFP2 as a basis for decadal forecasts.

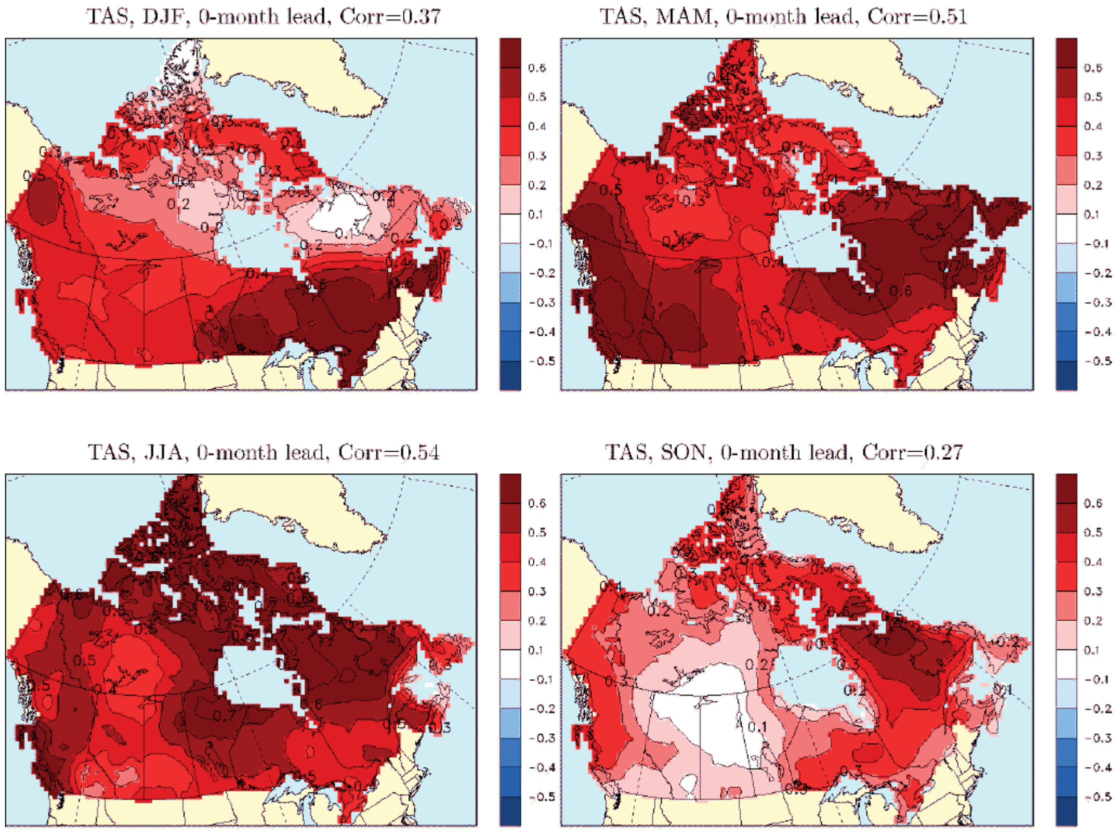

Figure C1: The correlation score of 0-month lead unweighted multi-model seasonal hindcasts of surface air temperature in Canada for 4 standard seasons. Correlations above 0.34 are statistically significant at the 5% level.

United States

Climate Prediction Center (CPC) of the National Centers for Environmental Predictions (NCEP) has provided operational seasonal forecasts over the U.S. since 1995. The seasonal forecasts are for anomalous probabilities for surface temperature and precipitation and for the below, normal, and above categories, and are released in the third week of the month. The target period of the forecasts is for the next 13 consecutive seasons [102].

Operational seasonal forecasts rely on a combination of empirical and dynamical prediction tools. Empirical prediction tools include an assessment of current trends relative to a 30-year climatology, Canonical Correlation Analysis (CCA) (Barnston 1994) etc. Dynamical seasonal forecasts are based on the Climate Forecast System (CFS) [37].

The atmospheric component of the CFS is the NCEP Global Forecast System (GFS) as of February 2003 with a horizontal resolution of T62 spectral truncation. There are 64 vertical levels in the atmospheric model with the top level at 0.2hpa. The oceanic component of the CFS is the GFDL Modular Ocean Model V.3. The domain of MOM3 is almost global extending from 74S to 64N. The meridional resolution of the ocean model is 1/3 between 10S and 10N, and gradually increases in the extratropical latitudes becoming fixed 1 poleward of 30S and 30N. The zonal resolution is 1. The CFS configuration of MOM3 has 40 layers in the vertical with 27 layers in the upper 400 meters. The vertical resolution is 10 meters from the surface to the 240 meters depth. Real-time forecast anomalies are provided to the LC-LRFMME on a monthly basis.

To establish model climatologies and allow an assessment of past skill, an extensive set of hindcasts is available. Hindcasts with CFS include a 15-member ensemble of nine month coupled forecasts run each month from 1982-2006. The real time forecast configuration includes twice-daily runs for 10 months, and forecast is constructed based on a 40-member lagged ensemble comprising of latest seasonal forecasts from past 20 days.

IRI

The International Research Institute for Climate and Society (IRI) currently produces a multi-model ensemble (MME) seasonal climate forecast based on inputs from several US-based 2-Tier atmospheric general circulation model (AGCM) forecast models. The relative weighting of the models in the MME is determined by retrospective forecasts using observed sea surface temperature. This system is about to be augmented by two new MME systems. The first MME system will continue to be 2-Tier but will use retrospective forecasts of SST from both statistical models and dynamical coupled models. The second MME system will have as inputs seasonal forecasts from coupled atmosphere ocean general circulation models (CGCMs) as well as at least 1 coupled model which utilizes a 2-Tier approach in the central and eastern Pacific but with predicted SST over the rest of the global oceans coming from a thermodynamic ocean model.

The current MME approach uses performance-based weighting of models to produce a 3-category forecast (i.e. terciles). The new MME approach will recalibrate models individually before combination and will include a spatial and local bias correction. The forecasts from the new MME will produce the full probability distribution.

South-West Pacific

Australia

The Australian Bureau of Meteorology has produced seasonal outlooks since the late 1980's. Currently a seasonal rainfall and temperature outlook for Australia is produced operationally based on statistical links between tropical SSTs and local climate [103]. However, it is felt that statistical approaches have essentially reached the limits of their predictive ability, particularly as climate change is invalidating the assumptions of stationary that is fundamental to statistical approaches.

The Bureau, in collaboration with CSIRO, has been developing successive versions of a dynamical coupled modelling system (called POAMA: Predictive Ocean Atmosphere Model for Australia; http://poama.bom.gov.au). The first version was implemented in Bureau operations in 2002 and generated forecasts of El Niňo sea surface temperature index. The POAMA system was upgraded in 2007 with version 1.5 and the operational products were extended to include forecasts of the sea surface temperature in the equatorial Indian Ocean [104]. Recently the products have been extended to give warnings of potential bleaching of coral in the Great Barrier Reef in the season ahead [105]. The version has been shown to have high skill in prediction not only ENSO and the IOD but also the "flavour of ENSO', ie the Modoki mode [106]. Regional rainfall and temperature forecasts are still based on the statistical system rather than POAMA at this point in time. Experimental rainfall products, such as probabilities of above median rainfall, from POAMA have been shown to be more skilful than those based on the statistical system based on skill measures such as the Brier skill score or hit rates, but the forecast reliability is low, i.e. the forecasts are too emphatic often showing probabilities in excess of 90%. Work is in progress to address this reliability issue so that POAMA rainfall can form the basis for the Bureau's seasonal climate outlooks, including a pragmatic statistical correction in the short term and investigating methods to increase ensemble spread in the long term.

A new version, POAMA-2 has been developed with increased resolution and improved physics. A comprehensive set of hind-casts are being generated. This includes a new ocean data assimilation system based on the multi-variable ensemble OI technique of Oke et al. [107] and using covariances calculated from a time evolving ensemble based on the ideas of Alves and Robert [54]. Preliminary results show a significant increase in SST skill in the Pacific and Indian Oceans. The hind-cast set will be completed in 2009 and the system implemented operationally in 2010. Developed of the POAMA-3 system is also on the way, which includes a new coupled model based on the UKMO Unified Atmospheric model and the GFDL MOM4, to be run at higher resolution that the current system. The ocean data assimilation system is also being extended to include the atmosphere and land surface, which will result in a multivariate ensemble coupled assimilation system.

Europe

France

Meteo-France started the production of an operational two-tier seasonal forecast system in 1999 after the ELMASIFA EC project. In 2004, after the DEMETER EC project, a fully coupled system has been set up.

The latest operational system uses an atmosphere model at TL63L91 resolution, a 2x2 deg ocean model with enhanced meridional resolution of 0.5 deg near the equator, and an OI-based ocean data assimilation system. These forecasts are part of the EUROSIP multi-model forecast system at ECMWF (see below).

Russia

The Hydrometeorological Centre of Russia is a designated GPC for long range forecasts. The operational system consists of a ten member ensemble produced with an atmosphere model with a 1.1 by 1.4 degree grid and 28 vertical levels. No ocean model is used, but SSTs are specified by persisting the initial observed anomalies for the length of the forecast. Hindcasts cover the 25 year period from 1979-2004.

UK

The UK Met Office began producing seasonal forecasts following the large El Niňo event of 1997/8 and was designated as a GPC along with 8 other centres in 2006. Model output is used in the UK and internationally by a range of government and commercial users, other forecast centres and the WMO Lead Centre in Korea.

During 2009 the Met Office will begin producing seasonal forecasts using the Global Seasonal forecasting system 4 (GloSea4). This system runs weekly and is based on the HadGEM climate model (Martin et al 2007 [57]) with a number of enhancements to model physics and incorporating the NEMO ocean model. The atmospheric component has a horizontal resolution of 1.25° latitude by 1.875° longitude, with 38 levels in the vertical. This represents a doubling of atmospheric resolution compared to the previous (GloSea3) system. The ocean component has 42 vertical levels and a grid-spacing of 1° latitude and 0.33° longitude near the equator, increasing polewards to 1°. Forecast initial conditions are produced separately for the atmosphere and ocean using an operational weather forecast analysis for the atmosphere and the FOAM ocean data analyses for the ocean. Perturbations are added to the atmosphere of each ensemble member to represent model uncertainties through stochastic physics parameter settings. Initial condition uncertainties are represented through lagged initialization.

ECMWF

The European Centre for Medium-range Weather Forecasts has run real-time seasonal forecasts with single-tier coupled ocean-atmosphere models since 1997. The latest operational system uses an atmosphere model at TL159L62 resolution, a 1x1 deg ocean model with enhanced meridional resolution of 0.3 deg near the equator, and an OI-based ocean data assimilation system. ECMWF is designated as a GPC, and model output data is also made available to member states, commercial customers and certain international projects. A selection of graphical forecast products are also available, some publicly and some restricted to WMO NHMSs for example.

ECMWF has also collaborated with France and the United Kingdom to produce an operational multi-model seasonal forecast system known as EUROSIP, comprising three operational European seasonal forecast models.