Science of Seasonal Climate Prediction

The Shine Dome, Australian Academy of Science, Canberra

2–3 August 2006

Report of workshop

Australian Government
Bureau of Meteorology

Wealth from Oceans
National Research Flagships
CSIRO

Managing Climate Variability
R & D Program

Australian Government
Bureau of Rural Sciences

Australian Academy of Science

Contents

Background

In order to provide a focus for the presentations and discussion at the workshop, the organising committee prepared a set of questions that highlight the key issues associated with the science of seasonal climate prediction. The questions were considered during the presentations and the panel discussions held at the end of each day. The set of questions has been slightly modified as a result of the workshop, but the scope of the original questions has been maintained. The response to each question has been prepared by the organising committee with advice from the presenters. The responses are aimed at being concise statements of the consensus views of the workshop, and it is hoped that they will assist scientists and program managers in setting priorities for future activity. The responses are seen to be an authoritative summary of the state of the science underpinning the application of seasonal climate prediction to a wide range of societal issues.

This report, which documents responses to the science questions about seasonal climate prediction, was prepared by the Organising Committee for the Workshop in consultation with all the presenters. The members of the Organising Committee were

- Colin Creighton, MCV
- Peter Hayman, SARDI
- Harry Hendon, BMRC
- Michael Manton, Monash University (Convenor)
- Chris Mitchell, CMAR
- John Sims, BRS,

and the presenters were

- Oscar Alves, BMRC
- Robert Fawcett, NCC, Bureau of Meteorology
- Peter Hayman, SARDI
- Harry Hendon, BMRC
- Arun Kumar, CPC, NOAA
- Simon Mason, IRI
- Peter McIntosh, CMAR
- Holger Meinke, DPI&F
- Scott Power, BMRC
- Ian Smith, CMAR
- Roger Stone, DPI&F
- Andrew Vizard, University of Melbourne
- Andrew Watkins, NCC, Bureau of Meteorology.

Report of workshop

What is the scientific basis for seasonal to inter-annual climate prediction in Australia and elsewhere in the world?

The scientific basis of seasonal climate prediction has been developed over the last century, and Australian scientists have made significant contributions to that development. It is recognised that seasonal climate anomalies result both from chaotic low-frequency variability of the atmosphere and from coupled interactions with the underlying ocean and land surfaces. The coupled interactions with the slowly-evolving ocean and land exert a sustained influence on climate anomalies extending over a season or longer, and thus they provide the potential basis for prediction with lead times of a season or longer. The atmosphere is particularly sensitive to tropical sea surface temperature (SST) anomalies, especially those that occur in association with the El Niño – Southern Oscillation (ENSO) phenomenon. The scientific underpinning of seasonal prediction in the Australian region is based on the observation that ENSO tends to evolve slowly and systematically and that the impact of ENSO on Australian climate is statistically robust. For example, the Southern Oscillation Index (SOI) and its associated SST indices such as NINO3.4 have very strong statistical lag correlations, so that for example winter values of the SOI and NINO3.4 are good predictors of their respective spring values. At the same time, it has been known for over a hundred years that Australian spring rainfall is well correlated with the SOI. These two statistical relationships provide the statistical basis for seasonal prediction in Australia.

Research over the last forty years has also explored and revealed the physical basis of the earlier-known statistical relationships associated with ENSO. Simplified models of the interactions between the tropical oceans and global atmosphere (known as Intermediate Coupled Models) are able to predict the onset and evolution of El Niño events with some success. Fully coupled ocean-atmosphere climate models (which can allow for all the dynamical interactions among the atmosphere, ocean and land surface) are now being used routinely to estimate the probability distribution of the climate some months ahead, and they show useful skill in predicting the onset, evolution and decay of ENSO events. Moreover, these models simulate the overall observed relationship between Australian rainfall variability and ENSO, thereby highlighting the physical basis for the statistical link between them. Recent research has also indicated potential predictability of Australian rainfall associated with the slow evolution of SST anomalies in the tropical Indian Ocean and from land surface conditions (such as soil moisture anomalies).

In summary, inter-annual climate variability associated with ENSO currently provides a firm scientific basis for seasonal climate prediction, and further research should clarify the roles of additional sources of potential seasonal predictability in the Australian region.

What is the impact of intra-seasonal variations on seasonal climate forecasts?

The Madden-Julian Oscillation (MJO) is the dominant mode of intra-seasonal variability in the tropics and its variations project on to seasonal and lower frequency scales. Thus the MJO is a potential source of noise in a seasonal prediction system. On the other hand, the MJO has some inherent predictability out to at least a couple of weeks and perhaps to a month, and so it has the potential to enhance the skill of seasonal prediction models. The predictability of the MJO appears to be associated with the slow eastward propagation and evolution of existing atmospheric circulation anomalies. There remains uncertainty about our capacity to predict the generation of MJO events, as their generation may be essentially random.

MJO activity is observed to be enhanced in the tropical western Pacific prior to El Niño events, and so there is speculation about whether the MJO acts as a trigger in the initialisation of those events. While it is not clear whether the MJO is more a source of noise or signal for the development of ENSO events, it is clear that models need to resolve the MJO in order to be effective at these time scales. It is also clear that the MJO plays a significant role in the climate of the tropics (e.g. monsoon breaks and modulation of tropical cyclogenesis) and sub-tropics (e.g. episodes of rainfall extremes in south eastern Australia), and that as we improve our understanding of the MJO and its predictability the skill of seasonal prediction should also improve.

What are the relative merits of statistical and dynamical prediction systems?

The statistical relationship between ENSO and Australian climate has been the basis of seasonal prediction systems in Australia for some decades. Statistical prediction systems are based on the historical relationship between local climate variables, such as rainfall and temperature, and large-scale drivers of climate, such as the Southern Oscillation (as measured by the SOI) and patterns of sea-surface temperature (SST) in the Pacific and Indian Oceans. Statistical systems can also be developed to relate user-relevant variables, such as wheat yield or stream-flow, to the large-scale drivers directly.

An advantage of statistical prediction systems is that they are relatively easy to develop and to explain to users. Indeed software tools have been developed to allow any user to explore the statistical relationships between the SOI and the rainfall distribution at any location in Australia. The simplicity of the systems has also meant that they can be readily coupled to more complex application and decision-support systems, such as plant growth models through the identification of analogue years. Analogue years are also useful in communicating to users the time evolution of anomalous events in the past. At present, statistical systems provide more accurate seasonal predictions of basic climate variables than dynamical systems are able to provide for Australia.

However, statistical prediction systems do have shortcomings. The statistical robustness of these systems is dependent upon the length and quality of the historical record, and these issues are highlighted when variables such as sub-surface ocean temperatures are used in a system. Statistical systems generally are based on an assumption of statistical stationarity, which does not properly account for decadal-scale variability or climate change trends. Many statistical systems are also linear, and so they cannot account for possible non-linear relationships between large-scale drivers of climate and local variables of interest. Because of the inherent averaging in the development of statistical systems, they generally cannot estimate the tails of the probability distribution as well as they estimate mean or median values.

The simplicity of statistical systems can itself lead to problems for users, because they can easily be developed by people without an understanding of the statistical limitations. In particular, "artificial skill" can be found in poorly designed systems, which show apparent skill when used with historical data but which have limited or no capability in predicting future climate variations.

It is clear that the statistical relationship between ENSO and Australian climate is significant, and so statistical prediction systems will provide the benchmark for more complex systems. Indeed statistical systems are currently the basis of operational seasonal prediction in Australia, and they appear to be hard to beat especially at short lead times. Increasingly, however, dynamical models are being introduced to provide longer lead-time predictions and greater scope for future development. While Intermediate Coupled Models are useful for exploring the physical processes associated with climate variability, fully coupled climate models are being developed as the future basis of seasonal prediction. As with numerical weather prediction (NWP), such dynamical models provide a foundation for continuing improvement as their scope and detail are enhanced. Dynamical models provide predictions of many aspects of the climate system and so their output can be readily adapted for a wide range of applications. The completeness of dynamical models also means that they can be used to explore the inherent limits of predictability of the climate system and to develop a deeper understanding of the fundamental non-linear processes that operate within the climate system.

Dynamical models are now used to generate an ensemble of predictions of the future climate, and so estimates of the probability distribution of all variables are obtained. In this way, dynamical models provide a direct approach to handling the inherently chaotic nature of the climate system. It is also expected that they will cope with future climate change more robustly than will statistical models.

How should seasonal to inter-annual forecast systems be evaluated?

In this section, we consider the evaluation of the skill or quality of a forecast system; the evaluation of its usefulness is considered later. Evaluation of systems occurs in two stages. When systems are being developed, there is a process of validation where the skill of hindcasts is assessed against the historical climate record. The historical data used for validation should be independent of the data used to develop the system, so as to avoid artificial skill. The future performance of a system can be estimated from the validation process.

The second stage of evaluation is the verification of forecasts of future climate states. Verification is part of the quality assurance of an operational system. However, because seasonal forecasts by definition accumulate slowly, verification results are usually available only for relatively short periods of time. Moreover, over a decade there may be only two or three ENSO events when a forecast system is strongly tested. Thus, verification results are not a particularly accurate indicator of the future performance of a system. On the other hand, verification results can provide an alerting mechanism for the detection of artificial skill in climate forecast systems.

It is clear that the evaluation of seasonal prediction systems is not straightforward. Some of the current statistical systems are based on 50 to 100 years of historical data, which provides a basis for a robust assessment of the skill of the system in hindcast mode apart from the impacts of climate trends and decadal-scale variability. However, for dynamical systems, there are generally insufficient independent historical data to carry out a full hindcast assessment, and it takes many years to accumulate sufficient data to assess the system in forecast mode. That is, the probabilistic nature of seasonal forecasts, together with the time taken to accumulate real-time assessments, creates inherent challenges.

The use of cross-validation techniques helps optimise the use of the limited amount of independent data available to validate statistical models. However, cross-validation of dynamical models can become impractical, especially if the models involve downscaling or bias-correction processes. The amount of computing time and power required to run dynamical models can limit the scope of validation, especially with a system involving model ensembles.

There are many different techniques for measuring the skill of forecasts, and they can have different behaviours as the skill of a system increases from zero to unity. The relatively low skill of current seasonal forecast systems can lead to confusion in the user community when different indicators appear to give quite different results. It is found that the relative behaviour of different skill scores can be usefully compared using simple theoretical models, such as a linear regression model.

Not only are there many different techniques for verifying models, but also the number of forecast systems continues to grow with time; for example, there are now about a dozen centres routinely running global ensemble prediction systems for seasonal forecasting. For these reasons, the World Meteorological Organization (WMO) has established a Standardized Verification System for Long Range Forecasts (SVSLRF) to provide some standardisation to the verification process. For probabilistic forecasts, the SVSLRF has a focus on the use of the Relative Operating Characteristics Score (ROCS) to measure the ability to discriminate between events and non-events, and on the use of reliability diagrams to measure the correspondence between predicted probabilities and observed frequencies. The Bureau of Meteorology is a Lead Centre for the SVSLRF.

It is appropriate to adjust the output of a dynamical model to remove climatological biases before the system is formally verified, but even this process can be difficult for highly-skewed variables like precipitation. The evaluation of ensemble prediction systems has additional complexity, as these systems have the potential to estimate detail about the expected probability distribution for many variables. It has been found that the accuracy of ensemble systems is improved by first fitting the ensemble to an analytical probability distribution function, rather than by scoring individual members of the ensemble.

What is the skill of current seasonal climate forecasts in Australia and elsewhere?

The skill of seasonal climate forecasts everywhere is limited by the observation that predictable signals are generally small compared with the inherent chaotic noise of the climate system. The Bureau of Meteorology routinely calculates reliability diagrams for its above-median rainfall forecasts accumulated across all Australian grid points. Its forecast probabilities, most of which lie between 0.40 and 0.65 (indicating only low to moderate resolution or sharpness), have shown quite acceptable reliability. However, measures of hindcast skill (such as ROCS, Linear Error in Probability Space (LEPS) and percent correct) indicate that the skill (essentially the degree of predictability) varies with location and season, and so regions like Queensland tend to have more reliable forecasts than Tasmania and western parts of the country. Moreover, much of the average skill of seasonal forecast systems comes from the successful prediction of the Australian climate during El Niño and La Niña events; Australian climate is less predictable in ENSO-neutral years. Verification is even more difficult to quantify due to the non-linear relationship between Australian rainfall and the Southern Oscillation Index (SOI); that is, the linear relationship is strongest in the La Niña years although major droughts are certainly well-correlated with El Niño events. The inherently limited skill of seasonal forecasts means that effective communication is needed between climate scientists and decision makers, so that the uncertainties are understood and appropriate risk management strategies are adopted in applications of the forecasts.

What is the potential predictability of seasonal climate anomalies over the Australian region?

Much research has been carried out on the development of seasonal climate prediction systems and their application to practical problems in agriculture and other societal areas. This research has been based on the knowledge that there is some potential predictability of seasonal anomalies in the Australian region. The nature of the predictability is mainly linked to the global-scale influence of ENSO, but there is some evidence of potential predictability from other large-scale drivers such as SST anomalies in the Indian Ocean. Thus, there has been a lot of research on the development and application of prediction systems and some research on seeking new sources of potential predictability, but there has been relatively little research on exploring the actual limits of potential predictability. Studies on predictability aim to determine the theoretical limits on prediction. These studies are important because no amount of ingenuity in a prediction system can overcome the inherent limits to the predictability of seasonal climate anomalies.

The limits of potential predictability can be studied with dynamical models by investigating the growth of small errors in the initial conditions of a model run. The results of such studies currently suggest that most variability in rainfall in the Australian region is associated with the chaotic and hence unpredictable components of the climate system. However, it is not clear whether the current estimates of seasonal predictability are low because of errors in the estimation techniques (e.g. systematic errors in the dynamical models) or because the inherent predictability of the climate system is low. Some studies of observed predictability associated with SST anomalies imply that some further gains in predictability are possible. Much more research is needed to clarify the limits to predictability through modelling studies and through the statistical analysis of the observed climate system.

In recent years, seasonal prediction systems in Australia have been extended to include temperature as well as rainfall. Not only is temperature an important influence on many societal and natural systems, but it also has much greater spatial coherence than rainfall. Thus temperature appears to have greater potential predictability, and the limits of this predictability need to be explored.

What is limiting the skill of seasonal predictions?

The skill of seasonal prediction models is inherently limited by the chaotic nature of the climate system; that is, any uncertainties in the initial state of the system lead to the non-linear growth of errors in dynamical prediction models. The skill of present coupled atmosphere-ocean dynamical models is further limited by the accuracy of the models. Indeed the current skill of dynamical models is comparable with that of purely statistical models, with the skill of both systems being mainly derived from the relationship between the SOI and climate variations. With these two limitations, the skill of coupled models should improve through two separate but related activities.

The history of numerical weather prediction (NWP), which has improved massively over the last several decades, has shown that, while demonstrable biases or systematic errors remain in a model, its performance can be improved. Moreover, the non-linearity of the models means that even a small correction can have a large (compounding) effect on the prediction skill. Another lesson from NWP is that, once a model has reasonable inherent skill in representing climate processes, the overall forecast accuracy can be markedly improved through data assimilation, which optimises the estimate of the initial state of the climate system. Data assimilation for coupled models is in its infancy at present, and so there are expected to be significant gains from the greater use of observed data in the initialisation of models. The availability of ocean data has increased greatly in recent years owing to advances in both satellite and *in situ* observing systems. Indeed the sparsity of historical ocean data is a limitation on the validation and even on the development of coupled models.

The overall skill of seasonal forecast systems is also limited by their capability to estimate the full probability distribution of the future state of the climate system. Because seasonal forecasts must be stated in probabilistic terms, we are really seeking the prediction of the probability distribution, with a particular aim of characterising the extent to which the predicted distribution departs from the climatological distribution. At present, ensemble prediction systems provide the methodology for estimating the probability distribution for all climate variables, and so we expect the overall value and skill of seasonal forecasting will be improved as we learn to optimise the application of ensemble systems.

What is the potential for improvements in skill and lead time in the near term?

There is potential for improvements in the skill and lead time of seasonal predictions. It can be argued that, following the initial success of intermediate coupled models in predicting ENSO events two decades ago, there was a tendency to over-state the progress in the science of seasonal prediction based on dynamical models. On the other hand, we now have a better understanding of the climate processes associated with seasonal scales of variability and a better understanding of the problems limiting the skill of dynamical models. A focused program of research on the development and application of dynamical models for seasonal prediction is expected to lead to improvements in seasonal forecasting, in comparison with the baseline level that has been established by statistical forecasting systems. The relative simplicity of statistical systems means that novel statistical methods will also continue to be developed and applied to practical problems.

In Australia, the collaborative Australian Community Climate and Earth System Simulator (ACCESS) program will provide the framework for dynamical prediction across all time scales. However, in addition to the development of the broad framework of ACCESS, there is a need for a specific program of research and development focused on priority issues for seasonal prediction. These issues include better understanding and prediction of the MJO, which is the dominant mode of intra-seasonal variability in the tropics, and better techniques for assimilating ocean and atmospheric data into coupled dynamical models, so that the initial state of the climate system is specified accurately. As with all model development programs, the modelling activity needs to be supported by more strategic research on climate processes and on basic questions of predictability. Indeed improvements in our understanding of climate predictability are required for us to determine the inherent limits on any seasonal prediction system.

The research and development required to improve the skill and lead time of seasonal predictions needs to be complemented by continuing enhancements to the products available to the user community. The detailed nature and scope of forecast products are determined by a balance of scientific feasibility with user requirements. Continuing communication between the climate and user communities is needed to ensure that balance is achieved.

How should prior estimates of forecast skill be made and how can they be used in real-time applications?

Because the reliability of seasonal forecasts varies with season, location and the prevailing large-scale environment, it is important that users understand these variations and account for them in their specific applications. Risk assessment is an accepted aspect of all economic activity these days, and so the uncertainty associated with a seasonal climate forecast is an additional risk to be included in the overall decision-making process for a user sector.

An estimate of the reliability of a specific forecast can be obtained from the analysis of hindcasts where the dispersion around the mean forecast can be estimated for given large-scale conditions. Ideally the dispersion will be small compared with the difference in the mean forecast from climatology. Because most skill in current forecasting systems is associated with the prediction of extreme El Niño and La Niña events, this condition is not always met at all locations.

With the continuing development of ensemble prediction systems to support seasonal forecasting, it is expected that real-time estimates of the dispersion around a mean forecast will become available. However, current research suggests that the simple spread of an ensemble is not the optimal estimate of forecast reliability.

What is the usefulness of current seasonal climate forecasts?

Forecasts are useful only if they can affect decisions in application areas, such as agriculture or water management. In Australia, the rural industries have been major users of seasonal forecasts, and this focus may have affected the nature of the operational forecasting systems currently available. Thus, the focus of seasonal prediction has been on rainfall and more recently on temperature. Moreover, the nomenclature used in forecast products has been developed in consultation particularly with the agriculture community and, within that community, more at the farm than the regional and industry level. On the other hand, the credibility or reliability of forecasts has not been compromised by artificially increasing the resolution or sharpness of forecasts in an effort to make them appear to be more relevant to the user community.

Ideally for users, all forecasts would have a large signal and high confidence. However, most of the skill in seasonal prediction is currently associated with the forecasting of the extreme events of El Niño and La Niña. The reliable prediction of these extreme events is somewhat offset by limited predictability when conditions are near the climatological mean. Another diluting effect on national predictions is that the forecasts are provided across the whole country, and so they extend to regions where there is little forecast skill beyond climatology. (It should be noted that knowledge of climatology is itself quite useful in managing climate risk.) The need to provide statistically robust predictions across Australia means that many sites have forecasts that simply reflect the seasonal climatology in some (or even most) seasons. Such variations in skill in time and location need to be communicated to and understood by users in order for them to make best use of seasonal forecasts.

As dynamical models are increasingly used to support seasonal forecast services, we expect the range of products to increase and hence the usefulness of the service should be enhanced. Model predictions can be improved through the application of downscaling techniques that can target forecasts to the variables and locations of particular interest to specific users. Ensemble prediction systems can be used to provide real-time estimates of the reliability of forecasts.

It is found that the apparent usefulness of a forecast can be sensitive to the way in which a forecast is applied. For example, there has been some consideration of the Wilks economic value score (EVS) as a measure of the usefulness of seasonal forecasts. Such examples assume that a user's actions depend upon a forecast probability threshold being exceeded, and so a forecast system with limited resolution or sharpness may only infrequently trigger actions by exceeding that threshold. Systems with limited sharpness also rate poorly with measures of skill like the Brier Score. Increasing the resolution or sharpness of forecasts increases the overall EVS of a forecast system (although it is important that this is done by introducing new sources of predictability, rather than artificially with a consequential reduction in reliability). In general, a forecast system adds value to an application only when a forecasted probability exceeds the application decision points, which may or may not be categorical. Thus, an application with a categorical decision point based on a forecast of above-median rainfall that falls outside the range of 0.4 to 0.65 will not benefit from the current forecast system of the Bureau of Meteorology. Whether the lack of sharpness in the current forecast system of the Bureau is predicated on the magnitude of the statistical association in nature or on the specific formulation of the current system remains a subject of further investigation.

For the EVS application, the use of a simple linear regression model as a theoretical seasonal prediction generator can demonstrate that in cases of limited inherent predictability the economic value is achievable only when the cost-loss ratio is near the climatological probability of the event being forecast, and that forecasts near climatology frequently are of limited value. However, the economic relevance of the approach can be questioned when the EVS is used as a measure of value relative to a perfect forecast rather than the absolute value of a forecast relative to a more realistic alternative such as climatology, and so important indicators such as the absolute profit of a decision-maker can be under-estimated. On the other hand, the Wilks model can be adjusted to compute other indicators, including indicators of risk. It is also worth noting that antecedent conditions are accounted for by varying the cost-loss ratio in the Wilks model. However, because the EVS is sensitive to the distribution of the cost-loss ratio, a single EVS analysis may not fully represent the impacts of antecedent conditions across a distribution of users.

Although the EVS can be used as an example of a theoretical application, it does not capture one of the major uses of climate information by managers of often-complex systems such as agriculture: risk management and planning across an integrated system. Seasonal prediction can help these decision makers to better prepare for the future by deciding on management strategies that either absorb or externalise risks posed by adverse climate events. Moreover, the value of a forecast does not depend on an individual decision-maker's responses alone, but rather on a series of responses by interrelated decision makers at farm, regional, national and international levels. It is well recognised in the scientific literature that trying to reduce the complexity of economic modelling by relying on only one or two scores of skill or value can often give a false measure of the real utility of a forecast system.

It is clear that deriving value from probabilistic seasonal forecasts is not straightforward, and further research should be conducted with close collaboration between forecast producers and users at all levels. Optimal value is derived when there is good communication between the climate and user communities, so that the nature and uncertainties of seasonal forecasts are understood and taken into account in a particular application. This approach recognises the dynamic relationship between information available through a forecast system and the management system to which the information is being applied. Thus the usefulness of seasonal climate forecasts should continue to evolve through improvements in prediction systems, management systems and the interactions between systems.

What strategies can be developed to optimise the value of seasonal climate forecasts?

In the scientific community, the advance in seasonal prediction associated with ENSO is regarded as one of the major achievements of the 20th Century. On the other hand, the benefits of seasonal prediction have been limited by the view that the probabilistic nature of the forecasts means that they may not be useful in practical decision-making. This view is partly explained by the well-known observation that humans are not intuitively good at dealing with probabilities. User surveys have shown that, while about 60% of primary producers take seasonal climate forecasts into account in their decision-making, the users tend to give them a low weight in comparison with other information and many are maintaining a 'watching brief' on forecasts. It is apparent that better communication between the climate and user communities is needed to enhance the value of seasonal climate forecasts. A range of tools, including simple graphs, can be used to communicate how changes in the conditional probabilities of events can be useful in practical decision-making and risk management.

The value of probabilistic seasonal climate forecasts can be improved by adapting the nature of the forecast to the specific application. In this way, the uncertainty associated with the climate forecast can be included in the overall risk management strategy for the application. It is necessary for users to appreciate both the scientific credibility and the relevance of a forecast for their application. Predictions of ENSO state during autumn is an example of a trade-off between relevance (farmers want the information in early autumn) and credibility (the uncertainty is reduced in late autumn and early winter). Related to the attributes of scientific credibility and relevance to decision-making is the sense of trust or legitimacy that users have in the forecast information, as well as the organisation and process through which the information is prepared and delivered. Thus, in addition to the development and application of mathematical and statistical techniques to optimise the value of seasonal forecasts, there is a need for continuing strategies to enhance communication between the climate and user communities, which extend from individuals to regional and national agencies and even to international organisations and programs. This approach requires effective links with intermediary groups such as extension agencies and the media, as well as with other scientific disciplines such as agriculture scientists, biologists and medical experts.

How does climate change and decadal variability affect the skill of current seasonal climate forecasts?

Temperatures across Australia, as well as globally, are increasing, and at least part of these trends can be associated with the enhanced greenhouse effect. There have also been recent trends in rainfall in parts of Australia, but the causes of such trends are not fully understood. In regions where there has been some focused research on the climate, such as south west Western Australia, there is some indication that the rainfall trends may be at least partly due to global warming. On the large scale, it is apparent that the frequency and intensity of ENSO events have been increasing since the 1970s, but the cause of these changes is not known. Moreover the impact of the changes on current seasonal forecast systems has not been clarified. Most statistical prediction models have been developed under the assumption of statistical stationarity of the climate, and so there is the potential for current (and future) conditions to fall outside the limits of the historical record on which a model was developed. Climate change can also lead to changes in the relationship between Australian climate variables (rainfall and temperature) and large-scale predictors of seasonal climate variations (SOI and SST), and such changes would generally not be captured in statistical prediction models. However, statistical methods can be used to adjust statistical forecasts for linear trends, estimated from a preceding base period.

While there is some uncertainty about the impact of climate change on statistical prediction models, dynamical models should not be affected by relatively slow trends and variations. Each time a dynamical model is run, it is initialised to the current state of the atmosphere and ocean, and the duration of a model run is short compared with the time scale of global climate change. Similarly, when dynamical models are run for only a few months ahead for seasonal forecasting, they implicitly account for naturally-occurring decadal-scale variations in climate.

Natural decadal-scale climate variations can be a further confounding factor for statistical prediction models that are developed from an historical record of limited duration. Analysis of the SST in the eastern Pacific or the SOI shows substantial decadal-scale variability, and hence substantial decadal variability in the occurrence and frequency of ENSO events. It is also found that there is corresponding variability in the correlation between Australian rainfall and the SOI. The slow modulation of the SST signal in the Pacific is measured by the Pacific Decadal Oscillation (PDO) (or the Inter-decadal Pacific Oscillation (IPO)), and the variations in PDO appear to vary consistently with the changes in correlation between Australian rainfall and the SOI. However, there is no evidence that the PDO is predictable at lead times beyond those associated with ENSO (i.e. beyond about a year), and so its variations can at best be used as a diagnostic tool to assess the reliability of a seasonal forecast. In principle, conditional probabilities could be used to refine a statistical seasonal forecast, but there are currently insufficient data to prepare a robust system.

What is the expected impact of climate change on seasonal climate forecasts in the future?

In Australia any question about the impact of climate change on seasonal forecasts is tightly tied to the impact of climate change on ENSO. Unfortunately there is no consistent evidence from climate change simulations using dynamical models as to how ENSO will change under the influence of the enhanced greenhouse effect. A significant reason for the lack of consistent evidence is that models currently have limited capability in accurately simulating the characteristics of ENSO. On the other hand, the quality of ENSO simulations continues to improve, and so there is some optimism that more robust indications of the impacts of climate change on seasonal forecasts should be possible in the future.

While there is a lack of consistent evidence on the future behaviour of ENSO, some modelling studies suggest that there could be significant changes in the seasonal rainfall in parts of Australia as the locations and intensities of synoptic weather systems change due to global warming and Antarctic ozone depletion. Indeed such studies suggest that some observed regional trends, such as the decease in rainfall in south west Western Australia can be partly linked to global climate change.

As in Western Australia where the water authorities are concerned about the downward trend in rainfall, changes in the seasonality of rainfall and temperature may start to become noticeable to natural resource managers in the near future. Such seasonality changes are likely to be difficult for current statistical prediction models to capture, and so some refinement may be necessary to adapt statistical models to measurable climate trends in future. The capturing of extreme events (such as heat wave temperatures) may be the most difficult problem as statistical models attempt to predict conditions outside the historical limits in which they were developed.

How should the combined effects of decadal variability and climate change on seasonal forecasts be managed?

As noted earlier, statistical prediction models have difficulty in accounting for both decadal-scale variability and climate change. Dynamical models should readily account for both these effects, as the models are initialised to the large-scale conditions observed at the start of a seasonal prediction model run, including the current concentrations of greenhouse gases and ozone. Moreover, the relatively short duration of a seasonal prediction run means that the model should not have to simulate long-term variations associated with climate change or natural decadal variations. On the other hand, dynamical models do need to account for climate processes that influence inter-annual variations (such as variable ocean currents and land surface changes), and the models need to be properly initialised to account for the initial states of these processes.

What areas of the science from an Australian perspective are likely to be the most fruitful for future research?

Australia has made significant contributions to the global research effort on the science of seasonal climate prediction. Much of the contribution has been first in documenting and explaining the causes of inter-annual variations in climate, and then in developing and applying statistical seasonal prediction models for Australian conditions. It is vital that future research continues to have a focus on improving our understanding and representation of key climate processes that affect seasonal climate variations (such as air-sea interactions of the MJO, land-atmosphere exchanges, and clouds and radiation over the ocean). Another important aspect of the improvement in seasonal prediction is the enhancement to the global climate observing system in recent years, especially in the ocean, and relevant research on the collection and analysis of climate observations will remain important for Australia. Enhanced observing systems, especially of land and ocean variables, are also necessary to improve our capacity to verify seasonal forecasts.

While interest in statistical systems will remain, significant advances are expected to arise from the continuing development of coupled dynamical models. The collaborative Australian Community Climate and Earth System Simulator (ACCESS) program provides an appropriate framework for the development of a national system for seasonal prediction. However, directed studies on issues relevant to initialising and predicting seasonal variations will be necessary to ensure that Australia maintains its current capacity in seasonal climate modelling. Another important component of dynamical model development will be studies to optimise the use of model ensembles to estimate the probability distribution functions of relevant climate variables, and hence to support the application of seasonal forecasts.

Australia suffers from the inherent variability imposed on our climate by ENSO, but this imposition can be partially offset by the inherent predictability associated with ENSO. However, we do not fully understand the nature and extent of the potential predictability of ENSO and other climate anomalies in the Australian region. Because the potential predictability places limits on the possible skill of forecast systems, further research on potential predictability involving both models and observed data is of strategic importance to seasonal forecasting in our region.

Australia already has an international reputation for applying seasonal climate forecasts to decision making and linking seasonal climate forecasts to simulation models. In order to continue to optimise the value of seasonal forecasts to the user community, joint research activities will be necessary on the interfaces between climate systems and user-application systems. This research will use appropriate mathematical methods (such as downscaling) to provide optimal interfaces to the models or techniques developed by the user community. The challenge of linking dynamical climate models to user-relevant variables (such as stream flow, wheat yield or sustainability indictors) in order to improve risk management will be a priority.

Program

Day 1 2 August

9.00am **Opening**
Professor Kurt Lambeck (President, Australian Academy of Science)

Scientific basis for seasonal prediction

9.10am **Statistical seasonal climate forecasting in Australia: An historical overview**
Presenter: Dr Roger Stone (Queensland Department of Primary Industries and Fisheries)

10.00am **The scientific basis of seasonal climate prediction**
Presenter: Dr Scott Power (BMRC)

10.50am **Coffee**

Limits to predictability

11.20am **Predictability limits for seasonal climate variability: Methodologies and current estimates**
Presenter: Dr Arun Kumar (Climate Prediction Center, National Centers for Environmental Prediction, NOAA)

Usefulness of seasonal forecasts

12.10pm **Applications of seasonal predictions in Australia**
Presenter: Dr Holger Meinke (Queensland Department of Primary Industries and Fisheries)

1.00pm **Lunch**

2.00pm **Imperfect forecasts and forecast value**
Presenter: Associate Professor Andrew Vizard (Melbourne University)

2.50pm **Towards more valuable seasonal climate forecasts for farmers**
Presenter: Dr Peter McIntosh (CSIRO Marine and Atmospheric Research)

3.40pm **Coffee**

4.10pm **Communicating skilful but uncertain seasonal climate forecasts**
Presenter: Dr Peter Hayman (South Australian Research and Development Institute)

5.00pm **Panel discussion of questions**

5.30pm **Close**

7.00pm **Buffet dinner**

Day 2 3 August

Evaluation of seasonal forecasts

9.00am	**Evaluation of forecast ensembles** *Presenter:* Dr Simon Mason (International Research Institute for Climate and Society, The Earth Institute of Columbia University)
9.50am	**Evaluating the skill of seasonal forecasts: Methods and problems** *Presenter:* Dr Robert Fawcett (National Climate Centre)
10.40am	**Coffee**
11.10am	**International standards of long-range forecast assessment** *Presenter:* Dr Andrew Watkins (National Climate Centre)

Impact of climate change and variability on seasonal forecasting

12.00 noon	**Intra-seasonal and decadal variability: Implications for seasonal prediction** *Presenter:* Dr Harry Hendon (BMRC)
12.50pm	**Lunch**
1.50pm	**Climate change and seasonal predictions** *Presenter:* Dr Ian Smith (CSIRO Marine and Atmospheric Research)

Future directions of science

2.40pm	**Future directions in the science of seasonal prediction** *Presenter:* Dr Oscar Alves (BMRC)
3.30pm	**Coffee**
4.00pm	**Panel discussion of questions**
4.30pm	**Close**

Statistical seasonal climate forecasting in Australia: An historical overview

Roger C Stone
Queensland Department of Primary Industries and Fisheries

Scientists at the Bureau of Meteorology initiated statistical climate forecasts as early as 1910 by applying Darwin pressure (now known to be linked to the El Niño - Southern Oscillation phenomenon) to provide a prediction of southern Australian rainfall. Although further experimental monthly forecasts were prepared by the Bureau (based on patterns of anticyclonicity), it was the remarkable increase in understanding of the mechanistic linkages between the Southern Oscillation and El Niño in the late 1960s and subsequent validation of earlier empirical analyses that led to the establishment of more scientifically acceptable seasonal climate forecast systems in Australia and elsewhere. Simple linear, lagged, relationships between the Southern Oscillation Index (SOI) and rainfall formed the basis of further developments in statistical climate forecasts, whether by using multiple linear regression-based systems or by applying slightly more sophisticated approaches such as principal component analysis, cluster analysis, or discriminant analysis to identify more subtle patterns of SOI activity (and rainfall patterns) over time as predictors in such schemes. Extension of such approaches, using empirical orthogonal functions of both predictors and predictands, applied to sea-surface temperature data formed a natural scientific progression from the earlier statistical attempts and form the basis of most of the currently applied systems in Australia. It has been particularly important to conduct independent verification in real time analyses and cross-validation methods to identify any potential for 'artificial skill', especially where a high number of predictors appear to provide an apparent increase in forecast skill but which, in fact, lead to a degradation of the forecast system (e.g. Nicholls, 1997). The need for more thorough understanding of the underlying mechanisms responsible for variation in climate patterns and also climate predictors has highlighted the value of coupled general circulation models (CGCMs) where, for example, a 100-year integration of a CGCM on NINO4 and all-Australian rainfall produced a correlation coefficient of -0.45 compared to the observed value of -0.53, thereby providing validity for those approaches that apply such systems in any statistical climate forecast application (e.g. Power *et al*. 2005).

References

Nicholls N (1997) 'Developments in climatology in Australia: 1946–1996' Aust. Met. Mag. 46, 127–135.

Power S, Haylock M, Colman R, and X-Wang (2005) 'Asymmetry in the Australian response to ENSO and the predictability of inter-decadal changes in ENSO teleconnections' BMRC Research Report No. 113 Australian Government Bureau of Meteorology Research Centre, Melbourne, 37pp.

Dr Roger Stone holds the positions of science leader of the Climate and Systems Technologies research unit within the Queensland Department of Primary Industries and Fisheries and also Associate Professor in Climatology at the University of Southern Queensland. He is also active in a number of WMO Commissions, notably as a Rapporteur within the Commission for Climatology and as the leader of two 'expert teams' within the Commission for Agricultural Meteorology. He holds a PhD from the University of Queensland.

The scientific basis of seasonal climate prediction

Scott Power, Harry Hendon, Oscar Alves and Lynette Bettio

Bureau of Meteorology

There is a huge body of evidence collectively indicating that seasonal climate anomalies linked to the El Niño-Southern Oscillation (ENSO) phenomenon can be predicted to some extent. The evidence from:

- observational analyses,
- mathematical models representing the physical processes underpinning climate variability ('climate models'),
- theoretical considerations, and from
- assessments of ENSO-based prediction schemes on independent data, will be reviewed here.

We will begin by reviewing observational analyses that provide insights into the cause and predictability of ENSO, and the impact that ENSO has on Australia. We will see that there are robust associations between ENSO and both synchronous and subsequent changes in climate generally, and Australian climate in particular. The lagged associations underpin predictability.

We will then turn our attention to the dynamics and predictability of ENSO itself. We will briefly review the progress that has been made in our understanding of ENSO, and the truly remarkable progress that has been made in our ability to simulate ENSO over the past twenty years. We will see that ENSO owes its existence to instabilities that exist naturally in the coupled atmosphere-ocean climate system and that predictability is also a feature of ENSO in mathematical models of the earth's climate.

Theoretical models used to encapsulate physical processes thought crucial for ENSO dynamics will then be described. The predictability of these simplified systems will be examined.

We will finish our review of the evidence underpinning predictability of seasonal climate anomalies linked to ENSO by briefly describing the success that ENSO-based forecast systems have had in predicting climate variability. A final comment on sources of predictability other than ENSO will be made.

Dr Scott Power is a Principal Research Scientist in the Bureau of Meteorology Research Centre. He led the development of the Bureau of Meteorology's first coupled atmosphere-ocean climate model, which was used to perform Australia's first transient global warming experiment. He then led the development of the Bureau's second model, which was subsequently used to conduct Australia's first climate model-based seasonal to interannual climate predictions. He has published extensively in the international literature on El Niño, climate change, climate prediction and climate services. He has worked in the Bureau of Meteorology for 15 years (as Head of Operational Climate Monitoring and Prediction, as Acting Head National Climate Centre, and as a Research Scientist).

Predictability limits for seasonal climate variability: Methodologies and current estimates

Arun Kumar

Climate Prediction Center, National Centers for Environmental Prediction, NOAA

Predictability limits for seasonal atmospheric climate variability depend on the fraction of seasonal variance that is due to factors external to the atmosphere (e.g. boundary conditions) and the fraction that is internal. Decomposition of observed seasonal variance into predictable (or external) and unpredictable (or internal) components, however, remains an outstanding (and often a controversial) issue. The importance of this decomposition is highlighted by the fact that the average skill of seasonal prediction has a fundamental limit that is determined by the ratio of external-to-internal variance.

In this talk reasons why limits to seasonal predictability should exist will be briefly discussed. Procedures for estimating atmospheric internal variability will be also outlined, and current estimates of seasonal predictability for surface temperature and rainfall over Australia will be presented.

Dr Arun Kumar graduated from Department of Meteorology, Florida State University, Tallahassee, Florida in 1990, and since his graduation has been affiliated with the National Centers for Environmental Prediction (NCEP). He is currently the Deputy Director of the Climate Prediction Center (CPC) at the NCEP. His research interests include understanding and assessment of seasonal climate predictability; development of application models for seasonal predictions; analysis of low-frequency trends; ENSO variability and predictions; multi-model ensembles etc. He has authored and co-authored more then 60 papers in peer reviewed journals.

Applications of seasonal predictions in Australia

Holger Meinke[1], Rohan Nelson[2] and Mark Howden[2]

[1] Queensland Department of Primary Industries and Fisheries/APRSU, [2] CSIRO Sustainable Ecosystems/APSRU

'Seasonal prediction (or forecast)' = ex ante assessment of likely climatic conditions for the season ahead
'Application' = Action taken in response to a seasonal prediction

Unless a seasonal prediction has 'relevance', that is, it addresses issues in ways that influence decision-making, the prediction will remain without impact and will thus be without value. Perception of forecast users, rather than just scientific precision, strongly influences the relevance of a forecast. Although farmers are one obvious client group, the value of a forecast might not depend on their response alone, but rather on a series of responses by interrelated decision makers at different scales. This responsiveness across multiple tiers of governance depends very much on the socio-economic and political context, local infrastructure including level of capacity, nature of scientific institutions, past experiences with climate forecasts and the agricultural system in question. To identify clearly clients and their decision points, it is helpful to classify them according to geographic and governance scale and the types of decisions that they make. Using economic decision analysis and adaptive governance as conceptual frameworks assists in identifying decision makers, the questions they need to answer, and therefore the types of climate information most useful to them. The needs of decision makers then become design criteria for applied climate science, assisting in the selection of the most appropriate and efficient data and tools to use. This implies that we need at least two pathways for effective applications. Firstly, a technically and scientifically sound prediction scheme that narrows the possible outcomes of the decision variable of interest to the decision maker. Such a scheme must therefore allow probabilistic assessments of alternative management options on secondary or even tertiary decision variables such as production, incomes and wellbeing. Secondly, we need institutional arrangements, structures and relationships that allow the use of a scientifically robust approach in a decision-making environment that goes beyond science. These institutional and social pathways are about engagement between scientists from diverse disciplines and decision makers across multiple tiers of governance. These pathways need to transcend the limitations posed by traditional institutional arrangements, structures and the vested interests of science institutions and decision makers. Such institutions need to embrace and foster pluralistic approaches that create an environment that values scientific knowledge (quantitative approaches) as well as qualitative methods. The combination of both is likely to yield more knowledge that either alone. In this presentation we will explore these issues. We will also provide some specific Australian examples.

Dr Holger Meinke is a Principal Scientist with DPI&F who manages an interdisciplinary research team. He has a Masters Degree in International Agricultural Development (TU Berlin, Germany) and PhD in Agriculture and Environmental Sciences (Wageningen University, The Netherlands). His work covers two major disciplines: agricultural systems sciences and climate sciences. He is a founding member of the Agricultural Production Systems Research Unit (APSRU), a joint venture between CSIRO, Qld Govt and UQ. He and his team focus on the development and application of agricultural systems models to deliver climate risk technologies for rural industries. They conduct climate variability/climate change scenarios analyses for risk assessments at field and farm levels but also as input into policy decisions. Their work includes strong national and international collaboration. Dr Meinke is a member of CLIVAR's Asian-Australian Monsoon Panel and a part of a WMO Expert Teams on forecast verification. He has 20 years of international research experience in agriculture, natural resource management, systems analysis and climatology.

Imperfect forecasts and forecast value

Andrew L Vizard

School of Veterinary Science, The University of Melbourne

The utility of probabilistic seasonal rainfall forecasts to assist with rational-decision making is highly dependent upon the reliability and the resolution of the forecasting system. Value score curves can be used to quantify the expected impact of unreliable or poor resolution forecasting systems for any given decision that an end-user may face. Using this approach, it has been shown that unreliable forecasts can impart negative value to users of the forecasts. Reliable forecasts should therefore be the primary aim of any seasonal rainfall forecasting system. Similarly, it has been shown that the value of forecasting systems with poor resolution is highly eroded and limited to decisions that are triggered by a small shift in the forecast from climatology. Analyses have demonstrated that the resolution of both the Australian Bureau of Meteorology seasonal rainfall forecasting system and the seasonal rainfall forecasting system based on the five phases of the Southern Oscillation Index is relatively poor, consequently constraining their utility to end users. Efforts should therefore be made to improve the resolution of these systems. However, any future minor improvement is unlikely to generate significant and widespread benefits to users. To deliver uniform and widespread value to users of forecasts, new lead indicators with markedly better predictive characteristics may need to be developed.

References

Vizard, A L, Anderson, G A and Buckley, D J (2005) Verification and value of the Australian Bureau of Meteorology township seasonal rainfall forecasts in Australia, 1997–2005. Meteorological Applications 12:343–355.

Wilks, D S (2001) A skill score based on economic value for probabilistic forecasts. Meteorological Applications 8:209–219.

Associate Professor Andrew Vizard has a background in research and consultancy. He is an Associate Professor of Veterinary Epidemiology at The University of Melbourne (part-time) and a senior consultant and former Director of the Mackinnon Project at the same university. The Mackinnon Project is recognised as a leader in delivering practical advice to farmers and agribusiness on a wide range of agricultural and economic issues. He is the author of over 50 scientific papers. He is also a director of several ASX listed companies and government instrumentalities.

Towards more valuable seasonal climate forecasts for farmers

Peter McIntosh

CSIRO Marine and Atmospheric Research

Two approaches to obtaining more valuable seasonal climate forecasts for farmers are described. The first involves obtaining a better understanding of the climate system by exploring the individual weather events that make up seasonal climate. A synoptic decomposition of rainfall events in North-West Victoria (Pook *et al*. 2006) indicates that there is one dominant synoptic system that is responsible for the majority of useful rainfall: the cutoff low. The seasonal frequency and intensity of these systems are then related to large-scale atmospheric and oceanic patterns. In addition, the sources of moisture and uplift necessary for rainfall are explored using a backward air-parcel tracking technique. The moisture source is found to be quite variable spatially, but is most likely to be from the oceans north of Australia. The number and strength of cutoff lows appears to be controlled by ocean temperatures to the south, and possibly also land temperatures. Vertical motion is also shown to be an essential part of the rainfall process.

The second approach involves simulation of the growth of a wheat crop in North-West Victoria, and examination of the application and potential value of different forecast systems. The importance of assessing on-farm value accurately using cross-validation techniques (McIntosh *et al*. 2005) is highlighted. It is concluded that a system to forecast rainfall might have some value provided it is accurate enough (Moeller *et al*. 2006). However, this might not be the best way forward, as it might only capture a modest fraction of the potential benefit of a forecast.

References

McIntosh P C, Ash A J and Stafford Smith M (2005). From oceans to farms: Using sea-surface temperatures in agricultural management. J. Clim. 18, 4287-4302.

Moeller C, Smith I, Asseng S, Ludwig F and Telcik N (2006). Assessing the economic value of seasonal climate forecasting – case studies from the wheat-belt in Western Australia's Mediterranean region. (Submitted to Agric. Forest Met.).

Pook M J, McIntosh P C and Meyers G A (2006). The synoptic decomposition of cool season rainfall in the south-eastern Australian cropping region. J. Applied Met. Clim. (in press).

Dr Peter McIntosh is a Principal Research Scientist in oceanography and climate with CSIRO Marine and Atmospheric Research in Hobart, where he has worked for 17 years. Prior to that he worked with the Bureau of Meteorology Research Centre in Melbourne. He has a PhD in Applied Mathematics and Oceanography from Monash University.

Communicating skilful but uncertain seasonal climate forecasts

Peter Hayman

SARDI

Whatever may be the progress of the sciences, never will observers who are trustworthy and careful of their reputations venture to foretell the state of the weather.
The Times, 18 June 1864; www.bom.gov.au/bmrc/clfor/cfstaff/nnn/nnn_climate_quotes.htm.

We are confronted with unprecedented opportunities to tune our agricultural systems in a way that improves their sustainable land use. We have a seasonal forecasting capability. We have started to think through how we can best use the knowledge that the next season is not a total unknown.
Hammer and Nicholls, 1996.

Information generated by climate science is only valuable if it is used. However using probabilistic seasonal climate forecasts in decision-making is proving to be harder than some of us first thought. The problem is not that people are unaware of climate forecasts. Climate science gains ample media attention. Words like El Niño have moved from oceanography to headlines, advertising copy and parliament.

A major challenge is that most of us are poor intuitive statisticians and this has implications in how we make general decisions under uncertainty (Burgman, 2005) and how we respond to seasonal climate forecasts in particular (Nicholls, 999). A further challenge is that assessing and making risky decisions is deeply embedded in the social setting and psychology of the decision maker (Hayman and Cox, 2004).

Communicating seasonal climate forecasts as a means to the end of better risk management is more than being clear about the message, using words carefully (e.g. frequency rather than percent chance) and designing better graphics such as box plots and pie charts. Nor is it simply a case of improving forecasts and improving the delivery of forecast information through tools such as Yield Prophet. These developments have all been helpful in the Australian context however they should be viewed as necessary but not sufficient. If communication is defined as '*the reciprocal construction and clarification of meaning by interacting people*' it will involve an ongoing engagement and dialogue with users.

References

Brugman, M A (2005) Risks and Decisions for conservation and environmental management. Cambridge University Press.

Hammer, G L, and Nicholls, N N (1996). Proceedings of the 2nd Australian conference on agricultural meteorology, Brisbane, 19–27.

Nicholls, N N (1999). Bulletin of the American Meteorological Society 80: 1385–97.

Hayman, P T and Cox, P G (2005) Drought risk as a negotiated construct, 113–126 in Botterill LC and Wilhite DA From Disaster Response to Risk Management. Springer.

Acknowledgements

Funding from GRDC and ACIAR, ideas from many colleagues in Australia and elsewhere who have risked reputations to promote climate forecasts as a means to the end of better management of climate risk.

Dr Peter Hayman is Principal Scientist, Climate Applications with the South Australian Research and Development Institute, prior to this he was an agricultural adviser and researcher with NSW Department of Primary Industries. Since the early 1990s he has worked with farmers and their advisers to apply the advances of climate science to improve the management of climate risk.

Evaluation of forecast ensembles

Simon J Mason

International Research Institute for Climate and Society, The Earth Institute of Columbia University

A critical review of methods for evaluating the quality of forecast ensembles will be presented. Most methods currently used require the forecast to be expressed as probabilities for discrete categories. There are a number of scores used for when there are only two categories, but options are more limited when the number of categories is three or more. It will be argued that the only valid score to use is the ignorance score because it is the only score that is strictly proper and local. A local score is one that scores a forecast only on the basis of the probability assigned to the outcome. The desirability of locality will be explained and defended. Graphical verification procedures are also used for forecasts of probabilities for categories. Reliability diagrams and ROC graphs are widely used. Some issues related to the comparison of graphs for different forecast systems will be raised.

It is often undesirable to have to categorise the ensemble, and so procedures for verifying ensemble distributions will be discussed. Appropriate ways of identifying whether this in any information in the ensemble spread (and higher moments) will be identified; procedures based on some form of correlation between ensemble spread and forecast accuracy will be rejected as inappropriate. Graphical procedures, such as the Talagrand diagram, will be considered. Some limitations of the Talagrand diagram will be raised, and the concept of 'complete calibration' introduced. Complete calibration refers to the reliability of subsets of forecasts, and is useful for identifying whether the reliability of a forecast is conditional upon the forecast.

Dr Simon Mason is a research scientist in the forecast division of the IRI. He has been working for the IRI since 1997, and has been responsible for assisting in the development of the operational forecast system. His main contributions to the IRI's operational forecast system are some of the GCM post-processing procedures, including recalibration and forecast combination schemes. Currently, his primary tasks are related to capacity building activities, including training and the development of the Climate Predictability Tool (CPT) software, to promote seasonal forecasting activities within Africa and elsewhere. Much of his research work over the last few years has been focused on forecast verification issues, and he has been leader of the WMO CCl Expert Team on Verification for the last four years. Before joining the IRI Mason was Deputy Director of the Climatology Research Group (CRG) of the University of the Witwatersrand, Johannesburg for South Africa. There he conducted research primarily on the variability and predictability of southern African climate. He joined the CRG from England in 1988.

Evaluating the skill of seasonal forecasts: Methods and problems

Robert Fawcett

National Climate Centre, Bureau of Meteorology

This presentation will discuss some of the issues and difficulties surrounding the evaluation of seasonal outlooks. It will cover validation (hindcast) versus verification (forecast) issues, selection of appropriate scoring techniques, the importance of cross-validation in hindcast skill assessment, and matters specific to the new coupled general circulation models (CGCMs).

The properties and relative merits of different forecast scoring techniques can be investigated by applying them to simple theoretical models, an approach which the National Climate Centre has found useful. Results arising from both analytical calculations and Monte Carlo simulations will be presented.

Dr Robert Fawcett is a senior meteorologist in the National Climate Centre, Bureau of Meteorology, Melbourne. His duties at NCC have included operational climate monitoring/prediction, client support and systems maintenance/development. He has recently become an Associate Editor of the Australian Meteorological Magazine, and is a co-author of a report on the operational verification of the Bureau's seasonal outlook service.

International standards of long-range forecast assessment

Andrew B Watkins
National Climate Centre, Bureau of Meteorology

When evaluating seasonal to interannual forecasts there are many and varied techniques that may be used, dependent upon what the user sees as most important for their line of work, or what is simply easiest for them to perform. While this is beneficial for the individual researcher or organisation, it can result in considerable difficulty when trying to determine the best techniques or methodologies used by models from different centres. Furthermore, inconsistencies in the way models are assessed can make it difficult to determine model usefulness to regional long range forecasters. For these reasons, the World Meteorological Organization (WMO) has defined a set of standards for the assessment of seasonal and longer range forecasts: the Standardised Verification System (SVS) for Long-Range Forecasts (LRF). The SVS-LRF recommends suitable diagnostics (e.g. Relative Operating Characteristics and reliability diagrams for probabilistic forecasts; Mean Square Skill Scores for deterministic forecasts), key variables (e.g. temperature at 2 metres, rainfall), key regions (e.g. the Tropics), and recommended verification datasets against which assessments should be performed. To further enhance consistency, the Lead Centre for the SVS-LRF (www.bom.gov.au/wmo/lrfvs/) provides basic computing subroutines, gridded verification data and a system for displaying results. Assessment of seasonal and longer range models, following the guidelines of the SVS-LRF, is required for those National Meteorological and Hydrological Services wishing to be accredited by the WMO as a Global Producing Centre of Long Range Forecasts.

Dr Andrew Watkins is a senior climatologist in the Bureau of Meteorology's National Climate Centre. As head of the Special Projects sub group, and a member of the WMO Expert Team on Long Range Forecast Verification, he manages the WMO Lead Centre for the Standardised Verification System for Long-Range Forecasts.

Intra-seasonal and decadal variability: Implications for seasonal prediction

Harry Hendon, Scott Power and Matthew Wheeler

BMRC

Variability with shorter and longer periods than those normally associated with El Niño-Southern Oscillation (ENSO) influence our ability to predict seasonal climate anomalies. Shorter and longer period variability may also be predictable, thereby contributing to improved seasonal prediction. This review will focus on (i) the dominant mode of tropical intra-seasonal variability, the 40-50 day oscillation or Madden-Julian Oscillation (MJO) and (ii) decadal ENSO-like modes.

The MJO accounts for about one third of the intra-seasonal variation of convection and winds across much of the equatorial Indian and Pacific Ocean. It influences onset and breaks of the Australian summer monsoon, tropical cyclone formation, and rainfall in subtropical Australia and elsewhere. Empirical prediction schemes for the MJO demonstrate useful skill out to about 15 days. Assessment of predictability of the MJO using a 'perfect model' suggests potential predictability with lead-time ~ 20-30 days, indicating the future possibility for enhanced prediction at ~1 month lead time. Seasonal variability of MJO activity, which is largely unpredictable, is an important source of noise for the coupled evolution of ENSO but also accounts for as much seasonal variance of rainfall and winds as does El Niño. Improvements of the representation of the physical processes that control the MJO (primarily moist convection and the interaction with the upper ocean) offer the hope of improved short-range dynamical seasonal prediction and will also contribute to more reliable El Niño prediction via more realistic ensemble spread.

ENSO's impact on Australia during the twentieth century exhibits large changes from decade to decade, and these changes are statistically linked to the Inter-decadal Pacific Oscillation (IPO). The IPO or the closely related Pacific Decadal Oscillation can be explained as the 'reddened' ocean response to atmospheric 'weather' and ENSO. Even though the IPO/PDO might well have limited predictability beyond interannual time-scales, substantial modulation of the Australian ENSO teleconnection can occur in association with the IPO. This occurs partly because the relationship between ENSO and all-Australia rainfall is non-linear. Physical explanations for this non-linearity, how it influences the character of decadal variability, and its implications for improved ENSO prediction will be reviewed.

Dr Harry Hendon received his PhD in Atmospheric Science from the University of Washington, Seattle USA in 1985. He since has held research positions at CSIRO, University of Colorado, and the Climate Diagnostics Center, USA. He has been Principal Research Scientist at BMRC since 2001. His interests include tropical intra-seasonal variability and its prediction, monsoon dynamics, and tropical ocean-atmosphere interaction. He is currently co-chair of the WMO WCRP Asian-Australian Monsoon Panel and member of the USCLIVAR MJO Working Group.

Climate change and seasonal predictions

Ian Smith
CSIRO Marine and Atmospheric Research, Water for a Healthy Country Flagship Program

The main source of seasonal predictability in the Australian region is related to variability associated with ENSO (El Niño Southern Oscillation) events. Climate change may affect these events in terms of frequency, duration, amplitude, phase locking to the seasonal cycle and the response of the hydrological cycle (Smith *et al*. 1997). A brief overview is presented of recent studies (e.g. Cane, 2005) which address this issue. These studies also indicate deficiencies in our understanding and ability to model ENSO events and point to priority research areas that need attention. Finally, the existence of significant trends in Australian seasonal rainfall over recent years (Smith, 2004) suggests that current baselines are likely to be inappropriate. An example is presented which indicates how this could affect current seasonal rainfall outlooks.

References

Mark A Cane, M A (2005). The evolution of El Niño, past and future. Earth and Planetary Science Letters 164 (2004) 1–10.

Smith, I N (2004). Trends in Australian rainfall - are they unusual? Australian Meteorological Magazine, 53(3), 163–173.

Smith, I N, Dix, M and, Allan R J (1997). The effect of greenhouse SSTs on ENSO simulations with an AGCM. Journal of Climate, 10, 342–352.

Dr Ian Smith is a Principal Research Scientist within the CSIRO Climate, Weather and Ocean Prediction Theme. His research includes modelling and diagnostic studies of Australian climate drivers, seasonal and multi-seasonal forecasting using a variety of methods, and the assessment of skill and value of forecasts. He is a coordinator of CSIRO's contribution to the Indian Ocean Climate Initiative (IOCI) research program, coordinator of the South East Australian Climate Initiative (SEACI) program on seasonal predictions, contributor to the Antarctic Climate and Ecosystems Cooperative Research Centre and an Honorary Research Fellow with The University of Melbourne.

Future directions in the science of seasonal prediction

Oscar Alves
BMRC

The socio-economic benefit from accurate seasonal forecasts now justifies the support for a range of activities from basic forecast model development to applications studies. Coupled model seasonal forecasts are now becoming competitive with more traditional statistical based forecasts. Coupled models offer the long term potential to provide seasonal predictions in an era of possible climate change, whereas, by definition, statistical approaches cannot be used if climate relationships are changing. However, many problems still exist with coupled models, most suffer significant climate drift and most have trouble adequately simulating some of the details of some fundamental modes of variability. This leaves a lot of room for improvement.

Coupled model forecast systems use the latest ocean and atmosphere observations for the initialisation of coupled forecasts. Over the last few years there has been significant improvements in ocean observing systems and these improvements are important for more skilful real-time forecasts. However, it is difficult to assess the skill of the real-time forecasts using retrospective hind-casts over say the last 25 years, because during the 1980's and 1990's the ocean observing network was relatively sparse compared with the last five years.

POAMA is the current operational dynamical seasonal prediction system at the Bureau of Meteorology. The system was developed jointly with CSIRO and Land and Water Australia. A new version, POAMA-2, has been built and will go operational early 2007. POAMA-2 has several enhancements and for the first time will provide rainfall forecasts in addition to El Niño forecast. In the longer term, versions of POAMA will use the ACCESS coupled model as one of its main components. The ACCESS model is the new earth system model being developed jointly by BMRC and CSIRO for a range including numerical weather prediction, seasonal prediction and climate change.

This talk reviews the current trends and issues in seasonal prediction and discusses the future directions of the science.

Dr Oscar Alves has a PhD in ocean modelling from University of Reading, UK, and he spent seven years at UK Met Office working on ocean modelling and four years at ECMWF working on the first ECMWF dynamical seasonal prediction system. He joined BMRC in 2000 as leader of the dynamical seasonal prediction project (POAMA). Since 2005 he has headed the Ocean and Marine Forecasting Group, which includes POAMA and a range of other ocean and climate related projects. His research interests include dynamical seasonal prediction, ocean modelling, data assimilation, and tropical climate variability.

List of acronyms

ACCESS	Australian Community Climate and Earth System Simulator
BMRC	Bureau of Meteorology Research Centre
BRS	Bureau of Rural Sciences
CMAR	CSIRO Marine and Atmospheric Research
CPC	Climate Prediction Center (USA)
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DPI&F	Queensland Department of Primary Industries and Fisheries (Queensland)
ENSO	El Niño – Southern Oscillation
EVS	Economic Value Score
IPO	Inter-decadal Pacific Oscillation
IRI	International Research Institute for Climate and Society
MCV	Managing Climate Variability Program
MJO	Madden-Julian Oscillation
NCC	National Climate Centre
NOAA	National Oceanic and Atmospheric Administration
NWP	Numerical Weather Prediction
PDO	Pacific Decadal Oscillation
ROCS	Relative Operating Characteristics Score
SARDI	South Australian Research and Development Institute
SOI	Southern Oscillation Index
SST	Sea Surface Temperature
SVSLRF	Standardized Verification System for Long Range Forecasts
WMO	World Meteorological Organization

This workshop was organised by the
National Committee for Earth System Science
Australian Academy of Science

Contact: Professor Michael Manton, School of Mathematics Sciences, Monash University
Email: michael.manton@sci.monash.edu.au

The workshop findings have been published online
www.science.org.au/events/seasonal