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A Survey of Seasonal Forecasting.

by

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Abstract

There are many benefits in knowing what seasonal climate anomalies are likely to occur in the future. In recent years there has been a substantial increase in the seasonal forecasting research and development activity needed to provide such information, and in the provision of real-time predictions. This paper provides a selective overview of current methods and examples.

1. Introduction

A seasonal forecast is a prediction of the value of some quantity (typically, surface temperature or rainfall) when averaged over a few weeks, at lead time of zero to several months. For example, a forecast issued in June could read 'there is a 70% chance that the rainfall in July-August-September will be larger than normal'. The methods and areas of application for seasonal predictions have increased substantially in the last few years, and the purpose of this paper is to provide an overview, mainly from a research and development point of view. This summary is necessarily selective: in particular, forecasting on a monthly timescale is not considered (see e.g. Harrison 1994, ECMWF proceedings 1996, and references therein). For other recent seasonal reviews, see e.g. Palmer and Anderson (1994), Moura (1994), Hastenrath (1995), Rodenhuis (1995).

The potential importance of reliable seasonal predictions has long been recognised. Monsoon forecasts based on pre-season observations were first attempted over a century ago, when Blanford started issuing Indian monsoon forecasts (Blanford 1884). Investigations of Indian monsoon predictability led Sir Gilbert Walker to discover many statistical connections between remote parts of the climate system (e.g. Walker 1924), including the now-famous Southern Oscillation (Walker and Bliss 1932). Early prediction efforts using statistical models based on sparse data and short timeseries often produced unreliable results. The availability of long (in many cases multidecadal) datasets with stringent quality control, fast computers, more advanced techniques and improved physical understanding of the climate system has led to substantial recent progress.

The following examples (some of many!) give some indication of the variety of atmospheric seasonal forecasts that are being produced, both operationally and experimentally. Further details about the methods, skills and predictors can be found in the references cited.

(A) Asia: predictions of the Indian monsoon onset and strength, based on a wide range of predictors, are issued by the Indian Meteorological Department (review by Kumar et al 1995). Predictions of rainfall in Japan and China have been produced (Sun 1994).

(B) Africa: rainfall forecasts are issued for several African regions. The 'Climate Watch Africa' bulletin produced by the African Centre of Meteorological Applications for Development (ACMAD) contains seasonal rainfall outlooks. West African July-August-September rainfall predictions have been available since the mid 1980s (Folland et al 1991), and East African 'short rains' forecasts have been issued experimentally by UKMO (see also Mutai et al 1996). Southern Africa rainfall predictions have been made (Landman 1994), and rainfall and temperature outlooks are issued regularly by the South African Weather Bureau.

(C) Brazil: a region where seasonal predictive skill is particularly high is the Nordeste region in Brazil, and various forecasts are produced for March-April-May NE Brazil rainfall (Hastenrath and Greischar 1993, Ward and Folland 1991).

(D) North America: operational long-range seasonal outlooks for US surface temperature and precipitation (Kerr 1994) based on several prediction methods (Barnston 1994, Huang et al 1996, Livezey et al 1996) are issued by the US National Centers for Environmental Prediction (NCEP). Predictions of Canadian temperature and precipitation have been produced (Shabbar and Barnston 1996).

(E) Australia: the Australian Bureau of Meteorology (BoM) issues operational seasonal outlooks for Australian rainfall.

(F) Europe: the analysis by Barnston (1994) showed evidence of modest but significant seasonal prediction skill in parts of Europe. Forecasts have been produced at the Swedish Meteorological and Hydrological Institute (Johansson et al 1996). Colman (1996) has made an experimental forecast for Central England Temperature.

(G) Global: experimental global predictions of rainfall, surface temperature and

500hPa anomalies are produced via a two-tier system (Bengtsson et al 1994) in a joint program involving Scripps Institution of Oceanography (SIO) and the Max Planck Institute for Meteorology (MPIM).

(H) Predictions of seasonal hurricane and tropical cyclone activity have been made (Gray et al 1992, Landsea et al 1994, Nicholls 1985, 1992, Chan 1994).

Typical predictors are sea surface temperature anomaly patterns, the Southern Oscillation Index (SOI), 500hPa height fields, the predictand in the previous season, etc. etc.

Sea surface temperature (SST) is the most commonly used predictor. Although persistence of anomalies is often assumed, the prediction of SST itself is an important aspect of seasonal forecasting. In particular, there is good evidence that tropical Pacific sea surface temperature anomalies are predictable at long lead times of many months: see section 4. Predictions of the SOI, which is closely related to Pacific SST changes, are also made routinely (Keppenne and Ghil 1992, Drosdowsky 1994).

Further details of many examples can be found in the NOAA Experimental Long-Lead Forecast Bulletin, which has been issued quarterly since 1992, and which is now available on the World Wide Web (see below). Other examples may be found in WMO long-range forecasting progress reports, and in reports from the International Research Institute for Climate Prediction (IRICP).

In some cases useful direct predictions of crop yields have been made. For example, the maize yield in Zimbabwe is strongly connected to rainfall, which in turn is related to sea surface temperature. The correlation between maize yield and sea surface temperatures in the east-central region of the tropical Pacific is over 0.6 at a lead time of 4 months. By using predictions of Pacific sea surface temperature anomalies, useful predictions of maize yield can be made (Cane et al 1994). Similarly, crop yields in Australia (Nicholls 1988, Rimmington and Nicholls 1993) and soybean futures prices (Keppenne 1995) have been related to the Southern Oscillation Index. Some crop yield predictions are included in the statistical seasonal outlooks produced by the Climate and Weather Research Laboratory at the University of Capetown. Further examples can be found in Moura (1994).

There is an ever-increasing amount of information about seasonal predictions and prediction methods available on the World Wide Web. A few examples are given below: others may be found using search engines or following links from those provided. (Note: the address details are subject to change.)

http://nic.fb4.noaa.gov/products/predictions/ for US seasonal outlooks by NCEP, and the Experimental Long-Lead Forecast Bulletin.

http://tropical.atmos.colostate.edu/forecasts/ for seasonal hurricane forecasts etc..

http://www.pmel.noaa.gov/toga-tao/ for information about El Niño and the tropical Pacific.

2. Why is seasonal forecasting possible?

We all know from experience that, beyond a few days, the detailed day-to-day changes in the atmospheric circulation are largely unpredictable. Even with a good model and accurate initial conditions, weather forecasts quickly diverge from the true atmospheric state. For seasonal forecasts we do not attempt to determine this high frequency unpredictable 'weather' component, but aim instead to predict some longer timescale, larger space scale component of the ocean-atmosphere system. A seasonal forecast system needs information about this slowly-varying part. For the atmosphere, much of this information lies in the boundary conditions (surface temperature, soil moisture, snow cover etc.). The most important of these is sea surface temperature, as discussed below. Other effects can be substantial (see e.g. Barnett et al 1989, Yang 1996 for snow cover, and a series of articles in Shukla 1993.)

The ocean has enormous mass and heat capacity compared to the atmosphere (in a vertical column, 10 (4) metres of ocean has about the same mass (heat capacity) as the entire overlying atmosphere), and changes more slowly. Through air-sea interaction involving heat, moisture and momentum exchange, the ocean affects the atmosphere both in the immediate vicinity and remotely via advection and planetary waves. This interaction is strongly affected by SST. Large scale SST anomalies tend to last for a few months, so the SST anomalies observed now can exert a systematic bias on the atmosphere in future months. To a lesser extent, current SST anomalies can also induce anomalies in the atmosphere/land system that in turn influence future atmospheric behaviour. Thus sea surface temperature is a very important predictor for seasonal forecasting.

To illustrate the persistent nature of sea surface temperature anomalies, Fig. 1 shows the correlation of observed monthly average sea surface temperature anomalies in the tropical Pacific (Niño3 region, 5N-5S, 90W-150W) with the anomalies in the same region some months earlier. Correlations remain above 0.7 for 3 months, and above 0.5 for 6 months. Thus a persistence forecast (that is, a forecast that assumes that anomalies observed now stay unchanged in the future) is a simple and useful forecast method for sea surface temperature. Persistence characteristics can depend on season and can vary decadally, as found by Balmaseda et al (1995) for the Niño3 region.

Persistence is effectively the sea surface temperature anomaly forecast used when predictions are made with atmospheric general circulation models. For lead times longer than a few months, the anomalies are usually gradually reduced in amplitude. Statistical methods to improve on simple persistence of SST anomalies are discussed in Ward et al (1993).

One other predictor that deserves mention is the quasi-biennial oscillation (QBO) in the stratosphere: unusual because it is not a surface boundary condition. There is evidence that the QBO state, which is predictable on seasonal timescales due to its slow oscillatory nature, influences the upper troposphere. In particular, the QBO is an important factor in hurricane activity prediction.

3. Examples of seasonal forecast methods.

3a. Statistical methods

By analysing historical data extending over several decades, statistical relationships between possible predictors and predictands can be established. Where significant connections are found, statistical prediction models can be developed and tested.

The recent availability of carefully produced datasets extending over several decades with wide spatial coverage, and the application of advanced statistical methods adapted from other fields, has led to an increase in the skill and coverage of statistical seasonal predictions.

One commonly used method that is simple to develop, test and apply is linear regression. Using the historical data, an equation like

$$rain \;=\; A_0 \;+\; A_1 \times predictor_1 \;+\; A_2 \times predictor_2 \;+\; ... \tag{1}$$

can be determined in a best-fit sense. Then, given pre-season values of the predictors, a rainfall prediction can be made. For example, given long records (e.g. several decades) of seasonal rainfall for some region and of SST, SST patterns that seem to be associated with that rainfall can be identified and tested as predictors.

A very important aspect of any sort of prediction is an assessment of the forecast skill and reliability. One method of cross-validation is to use half of the data to determine a prediction equation ('train the model'), then to make predictions of the rest of the predictand data and measure the skill. Alternatively, in the jack-knife validation method a forecast is made for each year in turn of the historical record by training the model using all data but that for the year to be forecast. (For broader discussions of forecast evaluation, see e.g. Livezey 1995, Potts et al 1996.)

Another technique that also requires only limited resources (e.g. a moderate personal computer) is discriminant analysis, that makes use of probability distributions based on the historical data. Ward and Folland (1991) provide a detailed description of both linear regression and discriminant analysis as applied to prediction of rainfall in NE Brazil, with validation using several different skill measures.

Yet another simple method is the use of optimal climate normals (Huang et al 1996). Basically, an average over the previous N years is used to estimate conditions for the next season, and the best choice of N is determined from historical data. This method takes advantage of slow changes that may occur on a timescale of several years.

A statistical technique that has recently found widespread application is canonical correlation analysis, which is used to relate spatial patterns in the predictor and predictand. (See e.g. Barnett and Preisendorfer 1987, Barnston 1994, He and Barnston 1996, Barnston et al 1996, Barnston and He 1996, Shabbah and Barnston 1996.) Other methods such as neural nets (e.g. Hastenrath et al 1995, Tangang et al 1996), singular spectral analysis (e.g. Keppenne and Ghil 1992) and principal oscillation patterns (e.g. Xu and von Storch 1990, Penland and Magorian 1993, von Storch et al 1995) have also been successfully applied. Most techniques are basically linear in approach. The advantages of nonlinear methods are often offset by data limitations which make it difficult to define the required parameters adequately.

Seasonal forecasts have been particularly successful for the March-May rainy season in NE Brazil (Ward and Folland 1991, Hastenrath and Greischar 1993), where the seasonal movement of the convergence zone is strongly controlled by sea surface temperature anomalies, principally in the tropical Atlantic ocean. Experimental real-time forecasts based on linear regression and discriminant analysis methods have been issued by the UK Meteorological Office since 1986. Preliminary (early February) and update (early March) forecasts are made for various combinations of observing stations: Fig. 2 shows the track record for Fortaleza/Quixeramobim.

The following is an abbreviated example of the content of a typical NE Brazil experimental forecast issued by UKMO:

Prediction of 1995 March-April-May rainfall
for Fortaleza/Quixeramobim, issued February 1995

The quint categories very dry (VD), dry (D), average (A), wet (W), and very wet (VW) are based on 1951-80 observed rainfall.

Current state of the Atlantic and Pacific SST predictor patterns: there are warm

SST anomalies in the south tropical Atlantic and cool SST anomalies in the north tropical Atlantic, which favour above normal rainfall; there are warm SST anomalies in the central and east tropical Pacific, which favour drier conditions.

linear regression:

$$\begin{aligned} \textit{normalised rain anomaly} &= 0.06 - 0.75Atl - 0.10Pac \\ &= +0.68 \quad (\textit{VW category}) \end{aligned}$$

discriminant analysis:

	VD	D	A	W	VW
probability	.02	.08	.05	.11	.75

AGCM: regional rainfall 30% above model climatology.

Best estimate forecast: VERY WET

(The updated forecast issued in March was for WET conditions, and the observed rainfall was in the WET category.)

This type of real-time forecast information has been used by Brazilian regional authorities to aid agricultural and hydrological management (Moura 1994).

The UK Meteorological Office issues similar forecasts for July-August-September rainfall in several regions in tropical west Africa, and for tropical east Africa October-November 'short rains' rainfall. Skill is good, but not as high as for North East Brazil. The rainfall-sea surface temperature link is more complicated, and other factors may have a significant effect. For the Sahel region, there are clear signs of interdecadal changes in rainfall that are related to interdecadal variability of an interhemispheric SST anomaly pattern (Ward et al 1993). Potential impacts and uses of the Sahel forecasts have been discussed by Hulme et al (1992).

Statistical forecast methods are inexpensive, requiring only a moderately powerful personal computer, historical data, and some readily available software. More widespread application of these methods, particularly by local meteorological services, is being encouraged.

Although the above examples refer to tropical regions, significant statistical forecast skill has also been obtained in extratropical regions. For example, Barnston has recently used canonical correlation analysis in a thorough and systematic investigation (Barnston 1994) relating northern hemisphere extra-tropical seasonal surface temperature and precipitation to SST, 700mb height, and prior values of the predictand. The most important predictor was found to be SST. He found skill 'good enough to be beneficial to a variety of users' for some locations and times of year. Skill was best for northern winter-spring in some North American regions, particularly in association with ENSO episodes.

3b. Atmospheric general circulation models

The remarkable increases in computer power in recent years have allowed the application of comprehensive dynamical atmospheric circulation models (AGCMs) to seasonal forecasting. AGCMs are physically-based and nonlinear, and should be able to simulate a wider variety of conditions than (mostly linear) statistical models which rely on some best fit to past experience. AGCMs do not rely on extensive historical data, and thus can provide forecast information for regions where data sparseness prohibits construction of empirical models. AGCMs are not limited to specific regions, but cover the globe: however, the model-specific forecast skill varies strongly with location and season. The AGCMs used for seasonal timescales generally have spatial resolution that is lower than that required for short-range numerical weather prediction, but sufficient to resolve and reproduce main climatic features.

Slightly different initial conditions can give very different individual results, so typically several AGCM runs are used to obtain an ensemble average. Where the scatter is substantial relative to the seasonal signal, a large (and expensive) number of ensemble members is needed to increase confidence in the predictions to expected levels. Estimates of the required ensemble sizes have been made by Brankovic and Palmer (1996).

Although AGCMs have been used extensively for forecasts on lead times up to one month, there has thus far been relatively little actual forecast work on the seasonal timescale (but see below). However, AGCMs have been used to assess potential seasonal predictability, by making ensemble runs with observed sea surface temperature. By analysing the results from an ensemble, comparing for example observed and simulated surface pressure, temperature, and precipitation, the amount of variability that is associated with SST variations can be estimated. The ability of such a model to reproduce observed year-to-year variations can also be assessed. The results are, of course, model dependent: low skill for a region in such an experiment does not necessarily mean that the region is unpredictable. Moderate skill in a region does however indicate some potential for useful predictions there. Such assessments show high levels of potential predictability in tropical regions, with lower levels elsewhere. In the extratropics, predictability is best in parts of North America. For assessments based on several recent years, see e.g. Kumar and Hoerling (1995), Kumar et al (1996), Stern and Miyakoda (1995), Dix and Hunt (1995), Brankovic et al (1994).

Extensive historical SST analyses are available: the UKMO Global Ice Sea Surface Temperature (GISST) dataset extends from 1871 to 1993 (Parker et al 1995), and has recently been revised (Rayner et al 1996). Multidecadal runs using GISST have been carried out at UKMO. Results based on 6 integrations from 1949-93 are described in a series of papers. Global maps of potential predictability for seasonal precipitation and mean sea level pressure (MSLP) are included in Rowell (1996): highest predictability is over the tropical oceans, with high predictability also over tropical island regions, northern South America and parts of Africa. Predictability is moderate over North America, and low (but sometimes significant) over Europe and mid-latitude Asia. The North Pacific and American region is analysed in more detail by Renshaw et al (1996), and the North Atlantic and European region is described in Davies et al (1996).

The recent completion of atmospheric re-analyses (e.g. by ECMWF, NCEP) for several years introduces the possibility of extensive predictability assessments that include consistent atmospheric initial condition information: such work forms a major part of the European PROVOST (PRediction Of Variability On Seasonal Timescales) programme. Richardson et al (1996) have presented some early results using a 9 member ensemble. Fig. 3 (taken from their report) shows spatial correlations R of simulated and observed 500hPa height fields for the northern hemisphere (20N-80N) for the Dec-Jan-Feb season, for the individual runs and the ensemble means. The AGCM runs used with end-of-November initial atmospheric conditions and observed sea surface temperature, for 1979/80 to 1989/90. Fig. 3 demonstrates how skill can vary from year to year. The most skilful year is 1982/83, when a very strong El Niño occurred: each individual member of the ensemble has positive skill (correlation ranging from 0.2 to 0.6). The highest ensemble skill (about 0.8) was attained in 1988/89, during a strong La Nina cold event in the Pacific.

Skill can be conditional: in some regions skill may be generally weak, but useful forecasts may be made in e.g. El Niño years. Extratropical skill is not necessarily linked to ENSO: from AGCM experiments there is evidence of substantial skill in non-ENSO years, and of weak skill in some ENSO years.

Such analyses are effectively forecasts with perfectly-predicted SST. For real-time AGCM forecasts some estimate of the SST evolution over the forecast period is needed. The simplest method is to persist the SST anomalies observed over e.g. one month prior to the forecast period. From 1994 on this method has been used at UKMO to provide additional forecast information for the NE Brazil and Sahel real-time seasonal forecasts. In the tropics the seasonal signal from different runs is quite consistent in some regions: for NE Brazil three-member ensembles have been used.

In some regions, notably the tropical Pacific, SST forecasts have been made that are more skilful than persistence (see section 4) at lead times beyond a couple of months. The SST forecasts are typically made separately, then used to force the AGCM in a two-tier strategy (Bengtsson et al 1993, Ji et al 1994). A comparison of the skill obtained for a particular AGCM using observed, persisted and forecast SST has been made by Livezey et al (1996). Hunt et al (1994) have used a two-tier strategy, as have Barnett et al (1995) by way of statistical atmosphere/SST relationships for the northern hemisphere.

4. El Niño

The largest interannual sea surface temperature variability signal is found in the tropical Pacific, associated with the cycle between warm El Niño and cold La Nina events. The SST anomalies in the equatorial Pacific Niño3 region (5N-5S, 150W-90W) shown in Fig. 4 indicate the nature of this variability: the peaks in 1976/77, 1982/83, 1986/87/88, 1991/92/93/94 correspond to warm events. El Niño has a strong interactive influence on convection in the tropical atmosphere, and hence on global circulation via tropical-extratropical interaction. (Ropelewski and Halpert 1987, 1996). This makes it the most important factor in seasonal prediction for many locations. Most of the examples given above involve El Niño as a predictor to some extent. The book edited by Glantz et al (1991) provides an excellent summary of El Niño behaviour, its global connections and its physical and societal impact. See also Glantz (1996). If El Niño could be predicted, then the accuracy and lead times for El Niño-associated forecasts can be improved. Thus an important element of seasonal forecasting research is the prediction of El Niño itself.

Through the WCRP Tropical Ocean Global Atmosphere (TOGA) Programme that ended in 1994, major advances in our understanding of tropical variability were made (TOGA, 1995). The importance of a network of observations of wind, sea surface temperature and subsurface ocean temperature was recognised, and the Tropical Atmosphere Ocean array was established in the tropical Pacific to provide in situ data (Hayes et al 1991). A wide range of models to simulate and predict tropical Pacific variability has been developed. This work continues as a major component of CLIVAR-GOALS (CLIVAR Science Plan 1995).

A common measure of the skill of an El Niño forecast model is the ability to predict sea surface temperature anomalies in the equatorial Pacific region. Several models have demonstrated significant SST skill at lead times of up to a year. The types of models range from statistical (e.g. Barnston and Ropelewski 1992) to simplified dynamical (e.g. Cane et al 1986) to coupled GCMs (e.g. Latif et al 1993, Ji et al 1996). The performance of several such models is discussed by Latif et al (1994) and Barnston et al

(1994). Further examples, with real-time predictions, can be found in the Experimental Long-Lead Forecast Bulletin.

El Niño prediction skill was high in the 1980s, but in the 1990s the pattern of Pacific SST evolution has been different (sustained warm Pacific conditions, a sequence of warm episodes) and skill has been lower. The warming in 1994 was particularly difficult to predict.

The impact of El Niño may depend on the nature of individual events. Ward et al (1994) identified two types of El Niño, with differing zonal SST gradient characteristics, that are associated with markedly different atmospheric anomalies.

5. Summary

There is substantial evidence that seasonal forecasting of meteorological and oceanic conditions is feasible, with significant levels of skill being attained. Skill is largest in tropical regions, but is also substantial in some extratropical regions, particularly during ENSO episodes.

For atmospheric conditions, the main predictor is sea surface temperature. SST anomalies can persistent for several months, and in that time they can exert a systematic bias on the atmosphere through air-sea interaction, which is strongest in the tropics.

The region of largest interannual SST variability is the tropical Pacific, and El Niño events in that region have a global impact and a strong influence on seasonal predictions. Fortunately El Niño is itself predictable several months in advance, and some schemes make use of this SST forecast information to increase the accuracy and lead times of predictions for land regions.

A wide range of prediction methods has been developed. Several inexpensive and useful statistical techniques are in use: such methods rely on past experience to make a forecast however, and hence are best applied in regions where accurate historical records are available. The use of atmospheric GCMs is becoming more widespread as computing costs decrease, although ensembles with many members may be required in extratropical regions to obtain reasonably reliable forecasts.

An important message from this selective review is that an expanding range of experimental and operational real-time forecasts is now available. The Experimental Long-Lead Bulletin provides a forum for the presentation and dissemination of a wide range of real-time seasonal predictions, and a substantial amount of information is available on the World Wide Web.

One aspect of seasonal forecasting that requires further research is the issue of determining the circumstances for which forecasts are most reliable: i.e. predicting predictability. Some areas of the extratropics are best predictable during ENSO episodes, for example, and there is evidence that different types of ENSO may have substantially different impacts. Similarly, particular combinations of other SST anomalies may generate particularly strong seasonal anomaly signals.

With several predictions of various types available for some predictands (notably El Niño), the possibility of combining different schemes to obtain better overall forecasts is being investigated (Fraedrich and Smith 1989, Casey 1995, Unger et al 1996).

Another aspect is the issue of interdecadal changes (Parker et al 1994). In the Sahel, for example, extended drought periods may be related to decadal changes in interhemispheric SST contrasts. A better understanding of such decadal variations and their possible impact on the skill of seasonal predictions could improve forecasts for such regions. There is also evidence (Latif and Barnett 1994, 1996) of decadal ocean-atmosphere interactions that may evolve in a predictable manner and thus offer the opportunity of useful predictions about likely variability several seasons in advance. A related issue is the impact of changes in climate variability induced by greenhouse gas changes (IPCC 1996).

A very important aspect of seasonal prediction that has not been discussed in this review is forecast application, through which the real benefits of seasonal forecasts are realised. The question 'what is a useful level of skill?' cannot really be answered in a purely meteorological or oceanic context, but depends on the application and requires interaction between the forecast providers and users. At present data available on this topic is very limited: however applications of seasonal forecasts are increasing and I hope a future reviewer will be able to discuss this aspect in detail.

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References

M.A. Balmaseda, M.K. Davey and D.L.T. Anderson, 1995. Decadal and seasonal dependence of ENSO forecast skill. J. Climate, 8, 2705-2715.

T.P. Barnett and R. Preisendorfer, 1987. Origins and levels of monthly and seasonal forecast skill for United States surface air temperatures determined by canonical correlation analysis. Mon. Wea. Rev., 115, 1825-1850.

T.P. Barnett, L. Dumenil, U. Schlese, E. Roeckner and M. Latif, 1989. The effect of Eurasian snow cover on regional and global climate variations. J. Atmos. Sci., 46, 661-685.

T.P. Barnett, M. Latif, N. Graham, M. Fluegel, S. Pazan and W. White, 1993. ENSO and ENSO-related predictability. Part 1: Prediction of equatorial Pacific sea surface temperature with a hybrid coupled ocean-atmosphere model. J. Climate, 6, 1545-1556.

N. Graham and T.P. Barnett, 1995. ENSO and ENSO-related predictability. Part II: Northern hemisphere 700mb height predictions based on a hybrid coupled ENSO model. J. Climate, 8, 544-549.

T.P. Barnett, L. Bengtsson, K. Arpe, M. Flugel, N. Graham, M. Latif, J. Ritchie, E. Roeckner, U. Schlese, U. Schulzweida and M. Tyree, 1994. Forecasting global ENSO-related climate anomalies. Tellus, 46A, 381-397.

A. Barnston, 1994. Linear statistical short-term climate predictive skill in the Northern Hemisphere. J. Climate, 7, 1513-1564.

A. Barnston, H. van den Dool, S. Zebiak, T. Barnett, M. Ji, D. Rodenhuis, M. Cane, A. Leetmaa, N. Graham, C. Ropelewski, V. Kousky, E. O'Lenic, and R. Livezey, 1994. Long-lead seasonal forecasts - where do we stand? Bull. American Met. Soc., 75, 2097-2114.

A. Barnston and Y. He, 1996. Skill of CCA forecasts of 3-month mean surface climate in Hawaii and Alaska. J. Climate, to appear.

A. Barnston, W. Thiao and V. Kumar, 1996. Long-lead forecasts of seasonal precipitation in Africa using CCA. Wea. Forecasting, to appear.

L. Bengtsson et al, 1993. A two-tiered approach to long-range climate forecasting. Science, 261, 1026-1029.

C. Brankovic and T. Palmer, 1996. Atmospheric seasonal predictability and estimates of ensemble size. Mon. Wea. Rev., to appear.

C. Brankovic, T. Palmer and L. Ferranti, 1994. Predictability of seasonal atmospheric variations. J. Climate, 7, 217-237.

H.F. Blanford, 1884. On the connection of the Himalayan snowfall with dry winds and seasons of drought in India. Proc. Roy. Soc. London, 37, 3.

M. Cane, G. Eshel, R. Buckland, 1994. Forecasting Zimbabwean maize yield using eastern equatorial Pacific sea surface temperature. Nature, 370, 204-205.

M. Cane, S. Zebiak and S. Dolan, 1986. Experimental forecasts of El Nino. Nature, 321, 827-832.

T. Casey, 1995. Optimal linear combination of seasonal forecasts. Australian Met. Mag., 44, 219-224.

J.C.L. Chan, 1994. Prediction of the interannual variations of tropical cyclone movement over regions of the western North Pacific. Int. J. Clim., 14, 527-538.

CLIPS, 1995. Climate Information and Prediction Services, WMO No. 832.

CLIVAR Scientific Steering Group, 1995. A study of climate variability and predictability: science plan. World Meteorological Organisation Technical Document 690.

A. Colman, 1996. Prediction of summer Central England Temperature from preceding North Atlantic winter sea surface temperature. Submitted to Int. J. Clim.

J.R. Davies, D.P. Rowell and C.K. Folland, 1996. North Atlantic and European seasonal predictabilty using an ensemble of multi-decadal AGCM simulations. UK Meteorological Office Climate Research Tech. Note No. 70. Submitted to J. Climate.

M.R. Dix and B.G. Hunt, 1995. Chaotic influences and the problem of deterministic seasonal predictions. Int. J. Clim., 15, 729-752.

W. Drosdowsky, 1994. Analogue (nonlinear) forecasts of the Southern Oscillation Index time series. Weather Forecasting, 9, 78-84.

ECMWF, 1996. Predictability, vol I, II. Seminar proceedings, European Centre for Medium Range Weather Forecasts.

C.K. Folland, J. Owen, M.N. Ward and A. Colman, 1991. Prediction of seasonal rainfall in the Sahel region using empirical and dynamical methods. J. Forecasting, 10, 21-56.

K. Fraedrich, 1994. An ENSO impact on Europe? A review. Tellus, vol 46A, 541-552.

K. Fraedrich and N.R. Smith, 1989. Combining predictive schemes in long-range forecasting. J. Climate, 2, 291-294.

M. Glantz, 1996. Currents of change: El Nino's impact on climate and society. Cambridge University Press.

M. Glantz, R. Katz and N. Nicholls (eds.), 1991. Teleconnections linking worldwide climate anomalies. Cambridge University Press.

N.E. Graham and T.P. Barnett, 1995. ENSO and ENSO-related predictability. Part II: Northern hemisphere 700mb height predictions based on a hybrid coupled ENSO model. J. Climate, 8, 544-549.

W.M. Gray, C.W. Landsea, P.W. Mielke and K.J. Berry, 1992. Predicting Atlantic season hurricane activity 6-11 months in advance. Wea. Forecasting, 7, 440-455.

M.S.J. Harrison, 1994. Monthly forecasting in the extra tropics. WMO Bulletin, 43, 201-207.

S. Hastenrath, 1991. Climate dynamics of the tropics. Kluwer Academic Publishers. 488pp.

S. Hastenrath, 1995. Recent advances in tropical climate prediction. J. Climate, 8, 1519-1532.

S. Hastenrath and L. Greischar, 1993. Further work on the prediction of northeast Brazil rainfall anomalies. J. Climate, 6, 743-758.

S. Hastenrath, L. Greischar and J. Van Heerden, 1995. Prediction of the summer rainfall over South Africa. J. Climate, 8, 1511-1518.

S. Hayes, L. Mangum, J. Picaut, A. Sumi and K. Takeuchi, 1991. TOGA-TAO: a moored array for real-time measurements in the tropical Pacific Ocean. Bull. Am. Met. Soc., 72, 339-347.

Y. He and A. Barnston, 1996. Long-lead forecasts of seasonal precipitation in the tropical Pacific islands using CCA. J. Climate, to appear.

J. Huang, H. van den Dool, A.G. Barnston, 1996. Long-lead seasonal temperature prediction using optimal climate normals. J. Climate, 9, 809-817.

M. Hulme, Y. Biot, J. Borton, M. Buchanan-Smith, S. Davies, C. Folland, N. Nicholds, D. Seddon and M.N. Ward, 1992. Seasonal rainfall forecasting for Africa. Part I: Current status and future developments. Intern. J. Environmental Studies, 39, 245-256.

M. Hulme, Y. Biot, J. Borton, M. Buchanan-Smith, S. Davies, C. Folland, N. Nicholds, D. Seddon and M.N. Ward, 1992. Seasonal rainfall forecasting for Africa. Part II: Application and impact assessment. Intern. J. Environmental Studies, 40, 103-121.

B.G. Hunt, S.E. Zebiak and M.A. Cane, 1994. Experimental predictions of climate variability for lead times of twelve months. Int. J. Clim., 14, 507-526.

IPCC, 1996. Climate Change 1995: the science of climate change. Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change. Edited by J. Houghton et al. Cambridge University Press, 572pp.

M. Ji, A. Kumar, A. Leetmaa, 1994. A multi-season climate forecast system at the National Meteorological Center. Bull. Am. Met. Soc., 75, 569-577.

M. Ji, A. Leetmaa, V. Kousky, 1996. Coupled model forecasts of ENSO during the 1980s and early 1990s at the National Meteorological Center. Mon. Wea. Rev., to appear.

A. Johansson, A. Barnston, S. Saha and H. van den Dool, 1996. On the level and origin of seasonal forecast skill in northern Europe. Submitted.

C.L. Keppenne, 1995. An ENSO signal in soybean futures prices. J. Climate, 8, 1685-1689.

C.L. Keppenne and M. Ghil, 1992. Adaptive spectral analysis and prediction of the Southern Oscillation index. J. Geophys. Res., 97, 20449-20554.

R.A. Kerr, 1994. Official forecasts pushed out to a year ahead. Science, vol 266, 1940-1941.

A. Kumar and M. Hoerling, 1995. Prospects and limitations of seasonal atmospheric GCM predictions. Bull. Am. Met. Soc., 76, 335-345.

A. Kumar, M. Hoerling, M. Ji, A. Leetmaa and P. Sardeshmukh, 1996. Assessing a GCM's suitability for making seasonal predictions. J. Climate, 9, 115-129.

K. Krishna Kumar, M. Soman, K. Rupa Kuma, 1995. Seasonal forecasting of Indian summer monsoon rainfall: a review. Weather, 50, 449-466.

W.A. Landman, 1994. A canonical correlation analysis model to predict South African rainfall. NOAA Exp. Long Lead Forecast Bull., 4, No. 3, 25-26.

C.W. Landsea, W.M. Gray, P.W. Mielke and K.J. Berry, 1994. Seasonal forecasting of Atlantic hurricane activity. Weather, 49, 273-284.

M. Latif and T. Barnett, 1994. Causes of decadal climate variability over the North Pacific and North America. Science, 266, 634-637.

M. Latif and T. Barnett, 1996. Decadal climate variability over the North Pacific and North America: dynamics and predictability. J. Climate, to appear.

M. Latif, T. Barnett, M. Cane, M. Fluegel, N. Graham, H. von Storch, J. S. Xu and S. Zebiak, 1994. A review of ENSO prediction studies. Climate Dynamics, 9, 167-179.

M. Latif, A. Sterl, E. Maier-Reimer, and M. Junge, 1993. Structure and predictability of the El Nino/Southern Oscilation phenomenen in a coupled ocean-atmosphere general circulation model. J. Climate, 6, 700-708.

R.E. Livezey, 1990. Variability of skill of long-range forecasts and implications for their use and value. Bull. Am. Met. Soc., 71, 300-309.

R.E. Livezey, 1995. The evaluation of Forecasts. In: Analysis of Climate Variability, H. von Storch and A. Navarra (Eds.), Springer-Verlag, pp 177-196.

R.E. Livezey, M. Masutani and M. Ji, 1996. SST-forced seasonal simulation and prediction skill for versions of the NCEP/MRF model. Bull. Am. Met. Soc., 77, 507-517.

A.D. Moura, 1994. Prospects for seasonal to interannual climate prediction and applications for sustainable development. WMO Bulletin, 43, 207-215.

C. Mutai, M.N. Ward and A.Colamn, 1996. Prediction of East Africa seasonal 'short rainfall' rooted in evidence for widespread SST-forced variability during October-December. Submitted to Int. J. Clim.

N. Nicholls, 1985. Predictability of interannual variations of Australian seasonal tropical cyclone activity. Mon. Wea. Rev., 113, 1144-1149.

N. Nicholls, 1988. El Nino Southern Oscillation impact prediction. Bull. Am. Met. Soc., 69, 173-176.

N. Nicholls, 1992. Recent performance of a method for forecasting Australian seasonal tropical cyclone activity. Aust. Met. Mag., 40, 105-110.

NOAA Experimental Long-Lead Forecast Bulletin (Ed. A. Barnston), issued quarterly since 1992.

T. Palmer and D. Anderson, 1994. The prospects for seasonal forecasting - a review. Quart. J. Roy. Met. Soc., 120, 755-793.

D.E. Parker, P.D. Jones, C.K. Folland and A. Bevan, 1994. Interdecadal changes of surface temperature since the late nineteenth century. J. Geophys. Res., 99, 14373-14399.

D.E. Parker, C.K. Folland, A. Bevan, M.N. Ward, M. Jackson and K. Maskell, 1995. Marine surface data for analysis of climatic fluctuations of interannual to century timescales. In: Natural Climate Variability (edited by D.G. Martinson et al.), National Academy Press, Washington DC, USA.

C. Penland and T. Magorian, 1993. Prediction of Nino3 sea surface temperatures using linear inverse modelling. J. Climate, 6, 1067-1076.

J.M. Potts, C.K. Folland, I.T. Jolliffe and D. Sexton, 1996. Revised 'LEPS' scores for assessing climate model simulations and long-range forecasts. J. Climate, 9, 34-53.

N.A. Rayner, E.B. Horton, D.E. Parker, C.K. Folland and R.B. Hackett, 1996. Version 2.2 of the global sea-ice and sea surface temperature data set, 1903-1994. UK Meteorological Office Climate Research Technical Note No. 74.

A.C. Renshaw, D.P. Rowell and C.K. Folland, 1996. ENSO responses and low frequency weather variability in the North Pacific/American sector 1949-93. UK Meteorological Office Climate Research Technical Note No. 73. Submitted to J. Climate.

D.S. Richardson, A.D.L. Evans, R.E. Evans and M.S.J. Harrison, 1996. The impact of observed atmospheric initial conditions on winter season predictability in the northern hemisphere extra-tropics. UK Meteorological Office, Forecasting Research Division Technical Report No. 196.

G.M. Rimmington, N. Nicholls, 1993. Forecasting wheat yields in Australia with the Southern Oscillation Index. Aust. J. Agric. Res., 44, 625-632.

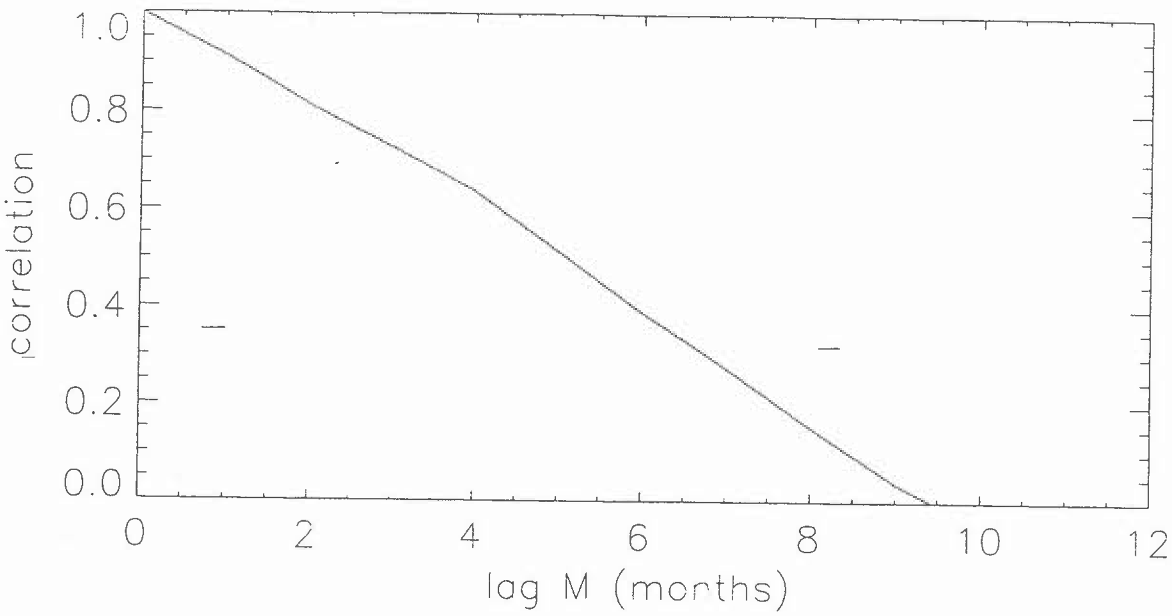

Figure 1: Lag correlation of observed monthly average sea surface temperature anomalies in the Niño3 region with the anomalies in the same region M months previously. Data from GISST, 1965-1990.

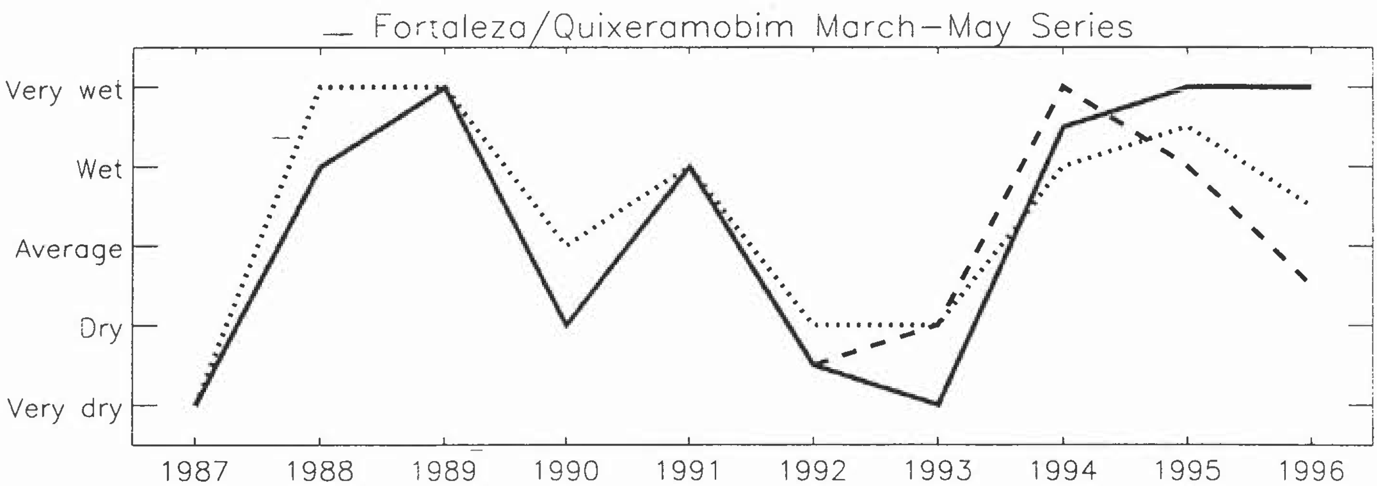

Figure 2: March-May seasonal rainfall at Fortaleza and Quixeramobim in Nordeste Brazil, in terms of five categories. Observed conditions are indicated by the solid line. Preliminary (dashed) and updated (dotted) experimental forecasts were issued by UKMO in early February and early March of each year.

Figure 3: Spatial anomaly correlation coefficients (ACC) between simulated and observed 500hPa height fields for the northern hemisphere (20N-80N) for the Dec-Jan-Feb season. The AGCM runs used end-of-November initial atmospheric conditions and observed sea surface temperature. Values for each of 9 realisations (solid bars) and of the 9-member ensemble mean (hatched bars) are shown. (From Richardson et al 1996.)

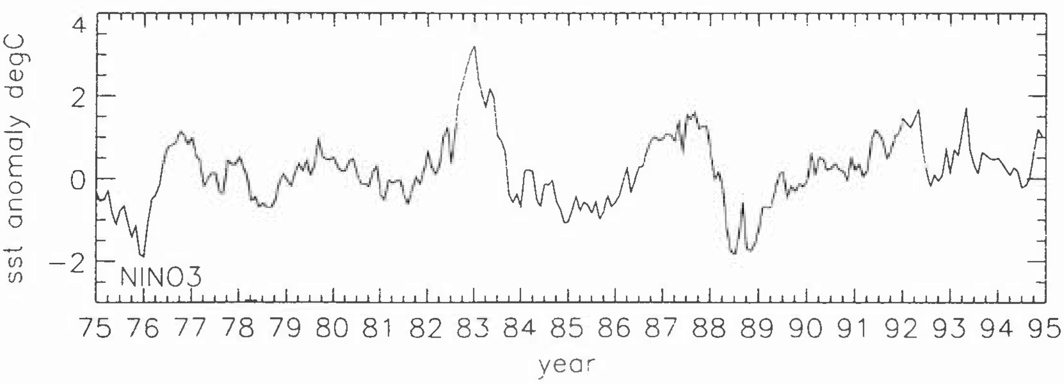

Figure 4: Sea surface temperature anomalies in the Niño3 region of the tropical Pacific. Long ticks indicate the beginning of the year indicated below. Data from GISST, 1975-1995.