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An overview of techniques for seasonal forecasting

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Abstract. A brief review of the state of seasonal forecasting at the end of the twentieth century is given. The physical basis of seasonal predictability is examined, and the implications of this for forecast strategies considered. The range of methods used for seasonal forecasting is described, with its division into empirical and numerical strategies, and methods for creating multi-model forecasts are discussed. Numerical prediction of climate anomalies is a new and emerging field of human endeavour, and some of its particular challenges are highlighted. Finally, the importance of the development of applications of seasonal forecasts is stressed, and the non-trivial nature of this task is noted.

1 Introduction

It has long been a dream of humanity to be able to predict the weather, and in particular to predict fluctuations in the weather on seasonal timescales. A very early example of a long range hydrological forecast is given in Genesis 41, where Joseph interprets a dream of Pharaoh to predict seven years of plenty followed by 7 years of drought. The forecast is acted on – food supplies are built up – and when the dry years strike, the nation of Egypt is well placed to cope with the poor harvests. Even several millenia ago, the potential practical benefits of long range forecasting were appreciated.

More systematic attempts to predict the weather substantially into the future had to await the development of early scientific thinking in Europe. Even so, early attempts were not overwhelmingly successful. One early pioneer was a German Abbot, Dr Knauer. He took careful and systematic weather observations during the period 1652–1658, and combined these with a concept of an astrologically inspired 7 year repeat cycle to produce a "perpetual weather calender", which was later modified to produce the so-called 100 year calender, popular in parts of Europe even today. Knauer was at least careful to point out that there were always exceptions and alterations to the weather patterns, and that the details for any particular day were not reliably predictable by his method. Even in the late nineteenth century weather forecasting was a much disputed art, with serious (and occasionally successful) attempts being made to predict storms months or more in advance, on the assumption that e.g. tidal influences from the moon were an important factor in the earth's weather patterns.

A conceptual understanding of why it is not possible to predict individual weather systems months or years into the future came only with the advent of

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chaos theory, starting with Lorenz (1963). Although chaos implies stringent limits for "deterministic" predictability of the atmosphere, that is, predictions of the actual sequence of weather events, it also implies that the unpredicatable behaviour of the weather nonetheless falls within a limited range of patterns – mathematically, there is an attractor in the system phase space. This "attractor", the structure of which determines both what is possible and how likely certain types of behaviour are, need not be constant in time. Seasonal forecasting, the attempt to predict future patterns of weather, can be understood as predicting changes in the attractor for weather, and hence shifts and changes in the probability distribution functions of weather (Palmer, 1993).

Empirical studies of long range atmospheric predictability did not wait for the development of dynamical understanding, however. At the end of the last century there was much interest in the relationships between solar activity and the weather, and practical interest in predicting Indian Monsoon rainfall led to studies of the large scale variability of pressure patterns in the tropics. Hildebrandsson (1897) seems to have been the first to point out the opposite variation of pressure between Sydney and Buenos Aires, and in 1924 Sir Gilbert Walker defined the "Southern Oscillation" as a see-saw in pressure across the Indo-Pacific region (Walker, 1924). Walker also described other modes of variability in the global atmosphere (including the North Atlantic Oscillation, the NAO), but it was soon found that the Southern Oscillation had the most potential for seasonal forecasting. By the 1930s, Walker and other scientists around the world had created empirical forecast schemes for the many parts of the world which have weather correlated with the SO, including South America, Australia, South Africa, Indonesia, Burma, China, the Caribbean, even Canada (Walker and Bliss, 1930). Nonethless, in the decades that followed interest in such empirical seasonal forecasting declined. This may be in part because the SO was less active in the middle part of this century (and so the apparent skill of the forecasts was lower), but it was also because of the lack of any firm physical basis for such large scale patterns of variability. Earlier motivating ideas such as solar and planetary influences were discredited, and nothing convincing emerged to take their place. It was only with the work of Berlage and then Bjerknes (1969) that a physical understanding of the Southern Oscillation emerged, and interest in it was rekindled. A good history of early research on the Southern Oscillation, from which much of this paragraph is derived, is provided by Allan et al. (1996). It is noteworthy that what are now known to be basically sound empirical forecasting schemes were considered somewhat dubious in the absence of any physical understanding: pure empiricism can be much strengthened by appropriate theoretical support.

This paper considers the state of seasonal forecasting at the end of the twentieth century. In Sect. 2, the physical basis of seasonal forecasting is considered, together with the implications this has for forecast strategies. Section 3 considers the different techniques that are used in seasonal forecasting today, and illustrates some of their successes and failures. Section 4 discusses the particular challenges facing the numerical approach to seasonal forecasting: this is the newest method of creating seasonal forecasts, and the one that is likely to dominate developments in the coming decades, yet much work remains to realize the potential of numerical techniques. Finally, Sect. 5 discusses the practical issues involved in the effective use of imprecise seasonal forecasts, and argues that the development of applications of seasonal forecasting is as much of a challenge as the scientific problems of producing the forecasts themselves.

2
The physical basis of seasonal forecasting

We start by giving some definitions of different uses of the word "climate", to help explain what we mean by seasonal forecasting. The concept of climate is very important in seasonal forecasting: due to chaos, we cannot predict exactly what the atmosphere will do during the coming season. If we are are going to make any sensible statements about "seasonal forecasts", we have to consider our language.

For the purposes of this paper, we define the "specific climate" of a weather variable as the probability distribution function of that variable for some specific period of time, beyond the range of deterministic weather forecasting. The probability density function (pdf) referred to is what we might call the true pdf – it represents the range of values which might occur which are consistent with the existing state of the universe. The specific climate is a function of the length of time between the specification of the pdf and the verifying time period (the lead time), but within a certain range (e.g. a lead time of between 20 days and several months) the specific climate is expected to vary only slightly with lead time.

The "long term climate" of a variable is the pdf of that variable averaged over a number of years. The specific climate may vary from year to year for physical reasons shortly to be discussed, but it is assumed that the climates of individual years are drawn from a statistical distribution whose properties are stably defined, at least over a specific time period. The "observed climate" of a variable is the pdf which is estimated from the individual observed values over a number of years. The observed climate will converge towards the long term climate as the number of years (i.e. the sample size) increases. The convergence is relatively slow, however, and so the observed climate is not always a very accurate estimator of the true long term climate. This is a particular issue if the climate is non-stationary, since in this case a long averaging period cannot be meaningfully used.

The essence of seasonal forecasting is to predict the specific climate for forthcoming seasons, and to highlight where that climate differs from the long term climate. To understand the physical basis of seasonal forecasting, we have to understand the factors that cause the specific climate of 1 year to be different to the specific climate of another. We also need to consider the extent to which these factors are themselves predictable, and on what timescales. Note that on this definition of seasonal forecasting we are not trying to predict "what will happen", since this is not amenable to scientific techniques. The biggest cause of variability in the actual weather between one year and the next, at least in mid-latitudes, is the chaotic, unpredictable part of the flow. The discussion in this section is about the physical causes of what can be said about a future season, i.e. a description of its specific climate, not about the variability which cannot be predicted.

From a global perspective, the most important reason why specific climate changes from year to year is variability in global sea surface temperature (SST). Ocean temperatures are more stable than land surface temperatures, due to the large heat capacity of water and the efficiency with which the top surface is continually mixed with the upper layers of the ocean. SST has a mean seasonal cycle, but anomalies of SST about this are of order 1 °C in magnitude, have spatial scales that can reach to 1000s of km, and timescales of one or several months. It is the relatively large space-time scale of SST anomalies that gives them the possibility of influencing the specific climate of the atmospheric circulation.

Sea surface temperature anomalies in the tropics are particularly important. Deep convection in the tropical atmosphere drives much of the global atmospheric circulation, and this convection is very sensitive to the underlying SST.

The sensitivity of evaporation (and hence latent energy input to the atmosphere) to temperature is higher at warmer temperatures, but the most significant factor is that weak horizontal temperature gradients in the tropical oceans make it easy for whole convective systems to be shifted large distances by relatively small changes in underlying ocean temperatures. SST anomalies in mid-latitudes have a local influence, but their impact on the large scale circulation of the atmosphere is thought to be much weaker than that of tropical SSTs, although not necessarily negligible.

Global SST is an important influence on atmospheric circulation, but this influence will only contribute to predictable changes in specific climate if the values of SST for the coming months are themselves predictable. A basic level of predictability clearly exists, as can be seen by the observed persistence timescales of SST anomalies, which are several months. Even if the growth and decay of SST anomalies is driven by unpredictable processes, which may be largely true for some parts of the ocean, their relatively long lifetimes give a physical basis for seasonal forecasting, at least in the short range.

For the tropics, and in particular for the equatorial Pacific, predictability of SST is enhanced by other processes. El Nino is the best known and most important manifestation of these partially predictable processes that drive changes in SST. El Nino is caused by coupled feedbacks between the equatorial ocean and atmosphere which can amplify anomalies in the system and produce large, coherent anomalies of SST. The corresponding atmospheric anomaly is the Southern Oscillation, as discussed in our historical introduction to seasonal forecasting. An important factor in El Nino is the large scale dynamics of the equatorial ocean, which has a timescale of months to years, and the evolution of which can be calculated by numerical models. The present state of the ocean has a substantial role in determining how the coupled ocean-atmosphere system will evolve over the coming months and seasons, although unpredictable variations in the atmosphere also play a role in what happens. The feasibility of seasonal forecasting is greatly helped by the partial predictability of El Nino, which is the biggest single cause of interannual variability in the global specific climate.

The land surface of the earth is also able to influence the atmosphere on seasonal timescales. Soil moisture plays the biggest role in this, although snow cover may also be important. Soil moisture can vary substantially from year to year, and change in soil moisture has a range of timescales which reach to months and beyond. Soil moisture has an immediate impact on the Bowen ratio (the partition between sensible and latent heat given off by a surface), either directly or through the mediation of plants, and this will directly affect local surface temperature, for example. Soil moisture can also influence the atmosphere on larger scales. At a continental scale, summer droughts and floods in the US have been shown to be influenced by preceeding soil moisture anomalies affecting rainfall (e.g. Beljaars et al., 1996).

Variation in snow cover may also be important for seasonal climate anomalies. At the end of the nineteenth century, variations in Eurasian snow cover were hypothesized to be important for regulating the Indian monsoon. It is now known that snow cover does not have a dominant influence on global atmospheric circulation (tropical SST is more important), but it is still likely that snow cover does play a significant role (Yang and Lau, 1998). The moisture left by the melting snow can have a bigger impact than the albedo/melting effects of the snow itself. As with soil moisture, anomalous snow or ice cover can of course have a large impact on local climate even if there is no feedback to the general circulation of the atmosphere.

There are a number of other factors which influence interannual variations in specific climate, but which are not so well understood. Variations in sea-ice cover have a large local effect, and may be important regionally. Vegetation will play a role in setting local climate at least, although to a large extent it responds either quickly to the availablity of moisture (hence adding no seasonal predictability) or very slowly (sustained drought over many years may change the whole ecosystem, but this is typically a decadal scale process, and depends on human activities as well as natural processes). Volcanic eruptions have the potential for drastic impact on climate in extreme cases, and even in the case of moderately large eruptions there is evidence for a response in the atmospheric circulation and in climate (e.g. Portman and Gutzler, 1996). Volcanic eruptions may not be predictable in advance, but in principle their influence should be taken into account after they have occurred. Other factors that may possibly influence climate at the earth's surface are stratospheric changes and changes in solar activity. The evidence for solar variability influencing the stratosphere is certainly suggestive (e.g. van Loon and Labitzke, 1998), and the stratosphere also has substantial interannual variability of its own such as the Quasi-Biennial Oscillation (QBO), which is often used as one of the predictors for hurricane activity. Physical mechanisms for any influence of the solar cycle are not well understood.

Knowledge of the physical basis of seasonal predictability helps shape our thinking on how practical forecasts might be made. Empirically, it tells us what factors we might expect to make the best predictors. For example, knowing that tropical SST is a major driver of atmospheric variability and has a decorrelation timescale of many months, tells us that we may be able to construct empirical forecast models, even for mid-latitude atmospheric flow, on the basis of tropical indices. Our physical knowledge gives us more confidence in such an approach than our predecessors had earlier this century.

For models, knowledge of which physical processes are important is crucial both for knowing which are the elements which must be included and/or improved, and for judging the level of performance we expect from our models.

Much remains unknown about seasonal predictability of specific climate and the factors that govern it. How sensitive is the impact of El Nino to the details of each individual event? How predictable is El Nino – does the unpredictable part of atmospheric variability mean that reliable predictions of El Nino are sometimes not possible at all? How important, and how predictable, are SST anomalies in the other tropical oceans? Which factors are most important in the European/North Atlantic Sector? How predictable are the Monsoons? Which factors control decadal variations in the earth's climate, and to what extent do they interact with interannual variability? How important are mid-latitude SST anomalies? How important are processes left out of most of today's models, such as volcanic aerosols and stratospheric changes? Although we believe the major elements are known, the scientific background for seasonal forecasting is still far from complete.

3
Methods for seasonal forecasting

There are two main strategies for trying to advance human knowledge, and in seasonal forecasting as in many other areas of science, a combination of the two may be the most powerful method. An empirical approach is to look at past data, and use this to construct predictive models for the future. A theoretical approach, on the other hand, is to attempt to calculate from first order principles or established approximations to them, how the climate system should behave.

A powerful theory should add substantially to any predictive power that can be obtained purely empirically – this is the nature of the scientific method. How powerful theoretical methods will become in seasonal forecasting remains to be seen.

As discussed in the introduction, empirical seasonal forecasting has a long history. The present day state of the art, however, can be simply illustrated by a few recent examples which span the range of methods used. An important point is that although, technically, one should only ever try to predict the "specific climate" of a variable in a seasonal forecast, many of the methods here produce a single definitive forecast value. This is best thought of not as a precise forecast, but a prediction of the approximate centre of a distribution. Implicitly, the "width" of the distribution allows both for the true width of the specific climate and for the influence of factors not considered in the forecast.

El Nino is the most important source of predictable interannual variability, and therefore a favourite target for forecasters. Sometimes the target (or predictand, what is being predicted) is the Southern Oscillation, the atmospheric counterpart of El Nino. Canonical correlation analysis (CCA) is one favoured technique which finds the linear relationship between predictors and predictands. More precisely, CCA finds the related patterns of variability which maximize the correlation between the predictor and predictand datasets. An alternative to CCA is singular value decomposition (SVD) which finds the patterns which maximize the explained variance in the relationship between predictor and predictand. An operational application of CCA to predict El Nino variability is described by Barnston and Ropelewski (1992). They use the forthcoming seasonal-mean values of SST in eight index regions as the predictand dataset. In their 1992 paper, the predictor datasets consisted of the same SST data for the present season plus the seasonal values of the global sea-level pressure field during the preceding year. The present operational system uses tropical Pacific SST, depth of the 20° isotherm and sea level height over the previous four seasons as additional input. Both predictor and predictand datasets are expressed (and truncated) as EOFs before the calculations. The predicted EOFs are then used to calculate the actual predicted value of SST in a region of the central Pacific.

Another example of a linear statistical scheme for predicting El Nino is the linear inverse modelling described by Penland and Magorian (1993). This uses the same dataset (the SST in the tropical Pacific and Indian oceans) as both predictor and predictand. The essence of the technique is to identify the (decaying) normal modes of variability in the system, and use these to predict the most likely future evolution. Because the modes are always damped, the long term tendency of the forecast is always to move towards climatology, but the non-self adjoint nature of the dynamical modes enables signals in specific regions to grow for a time (Blumenthal, 1991).

Not all empirical forecast schemes are linear. One approach is to train a neural network to predict El Nino development (Tangang et al., 1997). The input data for training consists of a single SST index, 28 coefficients describing the evolution of sea level pressure over the tropical Pacific during the previous year, and two inputs to define the seasonal cycle. Another approach is simply to look for analogues. Which year in the historical record is most like the present one? This needs to be guided by physical insight, of course, as to which fields are appropriate for defining analogues. The approach described by van den Dool (1994) is to use the time history of the global SST field during the previous year to define analogues, and to actually construct a more accurate analogue by a linear combination of historical cases. The resulting forecasts of an El Nino index are competitive with other methods. Details of these and other empirical methods for predicting El Nino can be found by looking at any recent issue of the Experimental Long-lead Forecast Bulletin (ELLFB – see references).

Many scientists are interested in predicting El Nino per se, but the real practical interest in seasonal forecasting lies in predictions of rainfall, temperature and other weather variables. There are many regions of the world where these are correlated with El Nino, and in a few places these correlations are strong, so one possibility is simply to construct a forecast based on someone else's prediction of El Nino. This can be done either quantitatively or simply as a qualitative statement. The alternative to such a "two-stage" statistical forecast is to seek a direct relationship between predictor and predictand variables. Examples of CCA based forecasts are those for tropical Pacific island rainfall (He and Barnston, 1996), surface climate in Alaska (Barnston and He, 1996), Sahel rainfall in West Africa (Barnston et al., 1996), and Canadian temperature and precipitation (Shabbar and Barnston, 1996). Typically the global SST field during the previous four seasons is used as a predictor, although sometimes prior values of atmospheric fields are also used. The choice of fields is usually motivated by physical considerations (see Sect. 2 of this paper), although sometimes apparently real predictive power is found from less expected sources, and this can be a motivation for further scientific investigation. A more straightforward approach to statistical prediction is to use multiple regression, where only a single predictand is targeted (or if a set of values is to be forecast, the prediction of each one is considered independently of the others). Examples of multiple regression are predictions of Nordeste rainfall in Brazil (Ward and Folland, 1991), US surface temperature and precipitation (Unger, 1996), and even English summer temperatures (Colman, 1997).

A general survey of the ability of CCA to predict seasonal anomalies in the extra-tropical northern Hemisphere is given by Barnston (1994). He found that statistical skill is mainly modest, but that for certain quantities, times and places "predictability is far above chance expectation and good enough to be beneficial to appropriate users". Typical of such a study is that much of the predictability is associated with El Nino variability, that North America is more predicatable than Europe, and that any predictable changes in European specific climate are very small. It must be remembered, however, that such a study is only able to find relationships which are strong enough in a linear sense to emerge from the analysis of a limited dataset. Because the linear relationship between European weather and El Nino is weak, it used to be thought that useful seasonal predictability of any form in Europe would be difficult to find. More recent results, both from data analyses and modelling studies, demonstrate that significant predictability is present in the European sector, although it remains less well understood than predictability in North America, and decadal variations may play a significant role (Palmer and Anderson, 1994; Stockdale et al., 1998; Venzke et al., 1999).

The second strategy for seasonal forcasting, the use of numerical methods, is less than 20 years old. An important breakthrough was the successful use of a numerical model for predicting El Nino variability (Cane et al., 1986). This model consisted of relatively simple models of the equatorial Pacific ocean and the tropical atmosphere, and the initial conditions for forecasts were prepared by using the observed variations of the wind field over the Pacific to create changed distributions of heat and mass within the ocean model's starting fields. The model components were designed to calculate only variations about normal conditions – the background climatology was simply imposed. The forecasts obtained were not especially accurate in the first 1–3 months, but the level of forecast skill decayed only slowly with lead time, and the ability of the model to predict El Nino variability 6–12 months ahead was impressive. Performance of this model configuration in the 1990 s has been disappointing, however, and much work has been done to improve the method of initializing the forecasts. The most successful results to date have been those incorporating satellite measurements of sea level into the initial conditions (Chen et al., 1998). Other relatively simple coupled ocean-atmosphere model forecasting systems have also been developed (Balmaseda et al., 1994; Kleeman et al., 1995).

A challenging task is to use more realistic models for El Nino forecasting. The reason that this is more difficult is that the general circulation models (GCMs) are required to simulate the full state of the ocean and atmosphere, and not just anomalies about some imposed mean value. Although today's atmosphere and ocean models are able to simulate reality moderately well, errors in the mean state can often be comparable to (or larger than) the year to year changes that are being studied. This, together with the extra cost and effort needed to work with complex models, has meant that more physically complete models have not been quick to dominate seasonal forecasting. One simplifying approach has been to replace the atmosphere model with a statistical scheme, so that only the ocean is modelled comprehensively (Barnett et al., 1993). Others have used empirical corrections of one sort or another in the atmosphere model or coupling to counteract model errors (Ji et al., 1996; Kirtman et al., 1997). Others have allowed model error to develop, and only used observed anomalies to initialize the model (Latif et al., 1993), or have subtracted estimated model errors after the calculation (Stockdale, 1997). The overall performance of coupled GCMs for forecasting El Nino has improved in recent years, and during the 1997/98 event it was the complex models that apparently provided the best real time numerical forecasts (Trenberth, 1998).

Coupled ocean-atmosphere models can be used to forecast El Nino and/or other anomalies in sea surface temperature. As with empirical forecasts, these must then be translated into predictions of atmospheric behaviour. This can be done by using atmospheric GCMs to simulate the response to a given SST anomaly, i.e. a two-stage forecast (Barnett et al., 1994). Two calculations made with an atmosphere GCM with very slight differences in the starting conditions will give very different results for the day to day evolution of the weather over a season, due to chaos. This is in fact what we want. By repeating the calculations many times to build up an ensemble of results, we can sample and hence estimate the pdf which defines the specific climate, as discussed in Sect. 2. Much research has been done on the ability of GCMs to reproduce seasonal climate anomalies when driven with observed SST anomalies (Palmer and Mansfield, 1986; Lau and Nath, 1994; Livezey et al., 1997). Several schemes which use models in this way, but taking predicted future SST rather than observed past SST, are now in regular use (see Barnston et al. in ELLFB, and forecasts on the web pages of the IRI – listed in references). In principle the GCMs can also include the response to other factors such as the initial soil moisture and snow cover, assuming that adequate data is available to define these.

The final level of modelling sophistication is to use a single coupled ocean-atmosphere model to calculate both the development of SST anomalies such as El Nino, and the atmospheric response to them (Stockdale et al., 1998). Again ensembles of forecasts are needed. Two advantages of this approach are that it helps sample the uncertainty in the SST forecast (each integration develops slightly different SST anomalies, which would not happen if a single SST prediction was used to force an ensemble of atmosphere-only integrations); and that the coupled interactions between ocean and atmosphere are more consistently represented. A potentially serious disadvantage is that errors in the coupled system may result in the atmosphere response being less accurate than in a two-stage calculation, where the mean value of the SST can be corrected before the main atmospheric part of the calculation. In practice this does not seem to be much of a problem, and results of the single-stage forecasting system at ECMWF during the last El Nino/La Nina cycle have been quite impressive (Stockdale et al., 1998; see also http://www.ecmwf.int).

How can the skill of such a variety of seasonal forecasting methods be assessed and compared? Unfortunately for the user, there is as yet no widely applied standard method of scoring seasonal forecasts. Such standard scores will be developed in the future, but there is a serious scientific reason why scores are difficult to assess. This is that the number of cases for which a seasonal forecast system can be tested is generally woefully inadequate. Empirical methods may be able to muster 50 years of cases, but care must be taken to avoid artificial skill due to the use of non-independent data for both deriving and testing any scheme. Dynamical methods generally have significantly shorter periods for which they can be tested. If a dynamical method relies on recent enhancements to the observing system, then the period may be very short indeed. As the observing system continues to evolve, non-stationarity is likely to remain an issue for testing numerical systems that use all available data. Non-stationarity in the earth's climate itself is a big challenge to empirical methods. A relationship that has been true for most of the past 50 years is not guaranteed to remain so, and indeed it was a long-term fluctuation in the behaviour of the Southern Oscillation which helped to suppress empirical seasonal forecasting for several decades in the early-mid twentieth century. For the case of El Nino forecasts, or certain "highly predictable" climate variables in certain parts of the tropics, even a moderate number of years will allow a reasonable estimate of forecast system skill, with the proviso that the future might be different. For the case of mid-latitude forecasts, or anywhere with a wide spread in the specific climate forecasts, assessing the forecast skill when only a single observed realization per year is available will take a long time.

Despite the difficulty of verifying seasonal forecasts, several points are already clear for the systems that exist today. Firstly they predict significant shifts in specific climate in many areas of the world, especially in El Nino or La Nina years. Secondly, there is some real skill in the forecasts: although the skill cannot be accurately measured, it is definitely greater than zero. Finally, the observations show that numerical forecasts are not perfect – i.e., the model predicted changes in climate are not perfectly correct. For empirical forecasts of changes in the centre of the climate distribution, the "error" or unexplained variance in the fit to observations remains substantial.

A final consideration for practical forecasting is the extent to which different forecasts can be combined to improve the quality or reliability of the prediction. This has been attempted for El Nino forecasts both by using multiple regression to map the output of a small set of forecasts to a single prediction, on the basis of past behaviour; and by simple averaging of a large set of forecasts without regard to supposed skill. The simple averaging seems to have been the more successful approach, although more work needs to be published in this area. For seasonal forecasts of atmospheric quantities, the best way of combining different forecasts is being actively considered both in the US and in Europe. There is particular interest in how to combine numerical forecasts from different models, and results from the PROVOST project in Europe demonstrate that the reliablity (and value) of seasonal predictions can be enhanced by the use of multi-model ensembles, again using a simple approach of combining different forecasts (Palmer et al., 2000). In ideal circumstances, if the skill and inter-correlation of several forecast methods were empirically known, then a statistically optimal forecast could be created. In practice, empirical estimates of the relative skill of different techniques will always have uncertainty, and hence robust methods of combining forecasts are needed. Work is still ongoing, but it seems likely that combined multi-model/empirical analysis will be an important part of seasonal forecasting in the future.

4
The challenges of dynamical modelling

Today's numerical models of the ocean and atmosphere have many imperfections which affect their use for seasonal forecasting. A brief outline of some of the issues is given here, together with a discussion of the pace at which improvements will be made. An important area that we will not discuss is the problem of initializing the coupled model, which is a major area of present research, and which depends on the development of observing systems as well as numerical techniques.

Atmospheric GCMs are well developed for use in short and medium-range numerical weather prediction. The systematic errors which used to exist in such models at lead times of 10 days have been substantially reduced since the early 1980s, for example, and systematic model errors are not thought to be a major problem for medium range forecasting. However, model errors are still large enough to cause problems for seasonal forecasts. For example, 6 month integrations of the ECMWF seasonal forecast model with observed SST show a systematic error in the 500 hPa height field over Europe which is comparable in amplitude with the seasonal anomalies which we would like to predict. Another aspect of atmosphere model behaviour that causes concern is the organization of tropical convection. In reality, large-scale organization takes place in the tropics, with regions of enhanced rainfall moving around the globe with a timescale of order 50 days. The ECMWF model handles these large scale disturbances quite well in 10 day forecasts (which is an improvement from 10 years ago), but they do not occur with the right sort of behaviour in seasonal length integrations. This may be a significant problem, both because disturbances like these may play a role in limiting the predictability of the ocean-atmosphere system, and because deep tropical convection is the mechanism through which tropical SST can influence the global atmospheric circulation. The treatment of tropical convection has a large impact on many aspects of atmospheric models, and improving parameterizations of this convection is still a challenge for the atmospheric modelling community.

When atmosphere models are coupled to ocean models, further issues arise. The most immediately apparent is model drift, the tendency for the SST (and then many other quantities) to drift away from realistic values. This drift accumulates over many months, and so is more serious for longer range forecasts than short ones. The primary reason is an imbalance in surface fluxes between the ocean and atmosphere. When an atmosphere model is run with a fixed SST field, it is effectively given an infinite heat source at this temperature – it can remove or add as much heat as it likes without any error being immediately apparent. When an ocean model is used, then of course the ocean is warmed or cooled according to the heat fluxes taken by the atmosphere. The typical heat flux over the ocean in the tropics is a small residual between a large input of solar heating and a large loss of latent heat by evaporation. Even apparently small relative errors in these terms result in significant errors in the small residual. The temperature drifts can be several degrees over a period of 6 months to a year. This makes predicting temperature anomalies of order 1 °C difficult, although as explained in Sect. 3 there are various ways of mitigating the problem. Nonetheless, the drift in SST is symptomatic of the errors in both component models, and unless and until the models are improved, imperfections in model-based seasonal forecasts are to be expected.

The rate of progress in numerical models for seasonal forecasting is uncertain. A pessimist might point out that the models have many errors which have been hidden by tuning: either by unintended natural selection or deliberate effort, models which partially compensate certain errors with other errors are favoured in model development. This means that as real improvements are made to individual processes within the model, the overall results may not improve as much as had been hoped, even after a retuning exercise. A further point is that as greater accuracy is required, the range of processes which need to be included might grow quite quickly, resulting in expensive and complex models which are difficult to work with.

An optimist might counter that although there are substantial issues in the improvement of numerical models, there is also substantial input of effort and resources. Seasonal forecasting is not alone in wanting better models, and a large community of climate scientists are working to increase our knowledge of physical processes within the climate system, and to provide appropriate numerical treatments. One might mention that although numerical weather prediction took some time to develop from its early stages, it is now a highly impressive and effective science. In the meantime, today's models are already good enough to build useful and credible seasonal forecasting systems, especially if care is taken to quantify and reduce the effect of errors by use of statistics and multi-model techniques.

5
Developing applications of seasonal forecasting

In areas of environmental prediction where a simple deterministic forecast can be made, a relatively clean line can be drawn between the forecast of some event and the use to which that forecast is put. For example, if a significant frost is forecast overnight, then a local authority will make sure the roads are gritted, a gardener may move some fragile plants to shelter, and a natural gas company may step up the pumping of supplies. All of these decisions can be made simply on the basis of a publicly issued forecast, without any particular dialogue between the weather forecaster and the users of the forecast.

Seasonal forecasting is not in this category. In most cases, unambiguous forecasts of specific events cannot be given, and this is particularly true in mid and high latitudes. The way in which the specific climate of a region changes from year to year is all that can be predicted. This is real information, and can and should be used to change real decisions. Communicating and using this information is not straightforward. The full information content of a probabilistic forecast consists not just of pdf's for countless weather variables, but also all of the cross-relationships between them – the exact correlation between rainfall, surface wind and temperature, for example, might matter for some applications.

Many potential users of seasonal forecasts already have decision making processes which are based on certain quantities. These may have been chosen not because they are optimal, but simply because they are available from observational records. For example, a power company might relate demand to total cloud cover rather than the amount of daylight, simply because climatological cloud data are available and radiative data are not. If such users want to use model-based forecasts, they may initially want to be supplied with seasonal forecasts of the quantities they are used to working with. In the long term, however, it may be advantageous to consider switching to use more relevant weather variables, since numerical models are able to offer a wider choice of variables than those commonly observed. In general, relating a forecast quantity to an event of interest through a chain of imperfectly correlated intermediates will degrade effective forecast skill. Specific to hydrology, flood conditions are more than a matter of rainfall, and simple predictions of rainfall amounts, even if correct, are insufficient to assess flood risk.

The ideal is a probabilistic forecast interface to appropriate decision making models. Decisions should be made, not on the basis of "what is most likely to happen", but on the basis of the range of possibilities and their associated likelihood. One specific decision making model which has been examined in the context of both medium-range probabilistic weather forecasting and seasonal forecasting is the cost/loss model (Richardson, 2000). Here it is assumed that a simple yes/no decision must be made to protect against some loss or damage. The cost of protection is C, and the protection is effective. If protection is not made, and some weather threshhold is exceeded, then damage occurs and a fixed loss L is made. The question is in what circumstances a probabilistic forecast can save money by reducing the expected loss. If no forecast is available, then the decision to protect will be based on the climatological probability of the threshhold being reached, and the size of C and L. If a calibrated probabilistic forecast is available (past performance can be used to estimate an approximate calibration – i.e. a mapping of the model calculated probability to the true probability), then the forecast probability is used instead of the climatological probability. If C is small and L is large, then we will protect even if there is only a small probability of damage occurring. If the climatological probability is relatively high, we will pay the cost of protection every year, and the forecast is of no use to us. If the decision is close to being finely balanced, climatologically speaking, then it is likely that forecasts of even moderate shifts in the probability of the event could be useful. A key point is that the threshholds and decision details will be different for every user, and the optimal use of numerical model forecast data is likely to depend on such details. Close working between forecast providers and forecast users is likely to be important.

A further point can be drawn out of the cost/loss model. An optimal decision can be made which minimizes the expected loss (or maximizes economic gain), in the sense that over a sufficient number of cases, use of the forecasts brings a benefit. But what if I cannot afford to take the loss this year? What if it will put me out of business, or if a failure will mean my family does not have enough to eat? Some actions we take not to maximize our overall gain, but to prevent the risk of a single bad year. A sensible and hard-headed approach to seasonal forecasts is much to be commended, and risks must always be considered. Taking different decisions each year according to a seasonal forecast may well increase the variance of income, compared with a conservative strategy of making the same decision every year.

Risks can be traded, however. For an individual who could make real beneficial use of seasonal forecasts on the average, but who cannot afford a financial risk of an occasional bad result, using weather derivative markets or other methods of trading risk might be a possibility. At its simplest, if by changing my business decisions I can on average make a profit, but am worried by increased variance in my cash flow, I may find an insurance company who guarantee me an extra profit every year, in return for a bigger payment in those years when the forecast comes right. Of course the insurance company will want a cut for taking the risk (and going to the trouble to negotiate the contract in the first place), but if the expected overall gain is big enough, then there will be profit enough for everyone. Already there is an active weather derivatives market in the US, which is driven mainly by companies wanting to protect their income against seasonal weather fluctuations, rather than to optimize real economic decisions. Seasonal forecasting has the potential to offer real benefits through enhanced decision making, and market mechanisms may come to play an important role in realizing some of these benefits.

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