The Scientific Basis for Seasonal Prediction

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Predictions are the life-blood of meteorology, and can be characterised by the timescale over which they are made. The timescale of 1-10 days is the domain of weather prediction; on this timescale it is possible to make forecasts about the weather for individual days. Seasonal prediction, the subject of this workshop, is concerned with forecasts, not of specific days, but of the properties of the atmosphere (and oceans) on timescales of months to possibly a year. (Although not discussed at all in this workshop, another important prediction problem concerns possible changes in the statistics of climate on decades to century timescales, as a result of anthropopgenically-induced changes to atmospheric composition.)

Weather prediction models are based on the known laws of physics as applied to the atmosphere. These laws are coded onto a supercomputer; given a set of atmospheric initial conditions, the computer code produces a definite atmospheric state for a date in the future. For weather prediction, the sea surface temperatures (SSTs) provide a fixed boundary condition for these forecasts. This is justified on the basis that such SSTs barely change on the 10-day timescale.

Such fixed boundary conditions are not appropriate on seasonal timescales. For example, at the beginning of 1997, SST anomalies were close to normal in the tropical eastern Pacific. By the end of 1997, SST anomalies in this region were up to 5C above normal. These ocean anomalies (associated with the 1997/98 El Nino event) had a dramatic impact on weather patterns, almost all the way around the world (*Webster and Palmer*, 1998).

In order to predict such SST anomalies, and their influence on world weather patterns it is necessary to couple the atmosphere models used to make weather forecasts, with similar computer models of the world's oceans. In such coupling, the SSTs are lower boundary conditions for the atmosphere, whilst in turn the atmosphere's surface winds and temperatures are upper boundary conditions for the ocean.

Unfortunately there is a "fly in the ointment", which prevents us making perfect forecasts on any timescale; more precisely it is a "butterfly" in the ointment - i.e. chaos theory. A chaotic system is one whose evolution is sensitive to the initial state. The butterfly effect is a paradigm, not literally true, which depicts this sensitivity in terms of almost the smallest imaginable disturbance (*Lorenz*, 1993).

On the other hand, chaos theory does not invalidate attempts at seasonal prediction. Although perfect deterministic forecasts are not possible on the seasonal timescale, reliable probability forecasts are. Such probability forecasts are possible by running so-called ensembles of seasonal forecasts. Each member of the ensemble is run from slightly different initial conditions, though each initial state is consistent with the available ocean and atmosphere observations (*Palmer and Anderson*, 1995; *Stockdale et al,* 1998).

An analogy can be made with a deck of cards. Suppose there is a deck of cards face down on the table in front of me, but I am not aware that the all the clubs have in fact been removed. I turn over the top card; let's say it is a heart. I turn over another card, let's say it is a spade. Continue this until I have turned over 30 cards. At this stage there should be more red cards than black cards roughly in the ratio of 2-1, and I might conclude that there was something anomalous about the deck of cards. Similarly, the first ensemble member of my seasonal forecast might predict above average seasonal-mean temperature over London. The second ensemble member might predict below average seasonal-mean temperature over London. If, when 30 ensemble members have been produced and the ratio of above average to below average temperatures is 2-1, I can deduce that there is likely to be something anomalous about the climate for that particular season. The probability of London having above average temperature will therefore be about 66%.

Suppose London actually experiences above average temperature. Does that make my probability forecast a good forecast? In fact nothing can be said about a probability forecast from just one case (except in the unusual situation where a probability of 0% or 100% is given). Probabilities can only be verified from a large number of past cases. A crucial measure of skill is given by the ensemble's "reliability". Consider a binary meteorological event E; for example "seasonal-mean temperature is warmer than climate" or "seasonal mean rainfall is less than two standard deviations below climate". Let me take all the occasions where I forecast E with 66% probability. Then my seasonal forecast system is reliable if, from this subset of forecasts, E actually occurred on 66% of occasions. This notion of reliability can be easily generalised for arbitrary probabilities and arbitrary events.

Reliable probability forecast can be more valuable that deterministic forecasts of uncertain accuracy (*Richardson*, 1999). This notion can be quantified using simple decision models. Consider a user who could incur a loss L if the event E actually occurs, but can take precautionary action, at cost C, to prevent L. Suppose the forecast is used to decide whether or not to take precautionary action. For a deterministic forecast, action is taken if and only if E is forecast. For a reliable probability forecast system, the decision process is more complex. For a user with a very low cost/loss ratio (C/L), the decision to take precautionary action should be made if E is forecast with almost any probability. However for a user with a high C/L, precautionary action should only be taken when the probability of E occurring is rather high. More generally, different users should base their decision process on different probability thresholds. In this sense a spectrum of users can utilise the whole probability forecast distribution.

Examples of "value" curves, based on the ECMWF coupled model system are shown in Fig 1. A value of zero indicates that a user could do as well if he/she only knew the climatological frequency of E. A value of unity is the value obtainable from a hypothetical perfect deterministic forecast. The values are based on temperature forecasts taken over the whole northern hemisphere.

At present, seasonal probability forecasts using coupled models are not as reliable as we would like them to be. One important factor is that forecast uncertainty can arise, not just because of sensitivity to initial conditions but also because of sensitivity to model formulation. In future research we are studying the effect on reliability of including more than one model formulation in our ensemble of integrations. Preliminary results suggest that such multi-model ensembles can provide more reliable forecasts than ensembles made with just one coupled ocean -atmosphere model (*Palmer et al*, 1999).

REFERENCES

Lorenz, E.N., 1993: The essence of chaos. University of Washington Press. Seattle, USA, 227pp.

Palmer, T.N. and D.L.T. Anderson, 1994: The prospects for seasonal forecasting. Q.J.R.Met.Soc., 120, 755-793.

Palmer, T.N., C. Brankovic and D.S. Richardson, 1999: A probability and decision model analysis of PROVOST seasonal multi-model ensemble integrations. Q.J.R.Met.Soc., to appear.

Richardson, D.S., 1999: Skill and economic value of the ECMWF ensemble prediction system. Q.J.R.Met.Soc., to appear.

Stockdale, T.N., D.L.T. Anderson, J.O.S. Alves and M.A. Balmaseda, 1998: Global seasonal rainfall forecasts using a coupled ocean-atmosphere model. Nature, 392, 370-373.

Webster, P.J. and T.N. Palmer, 1998: The past and future of El Nino. Nature, 390, 562-564.

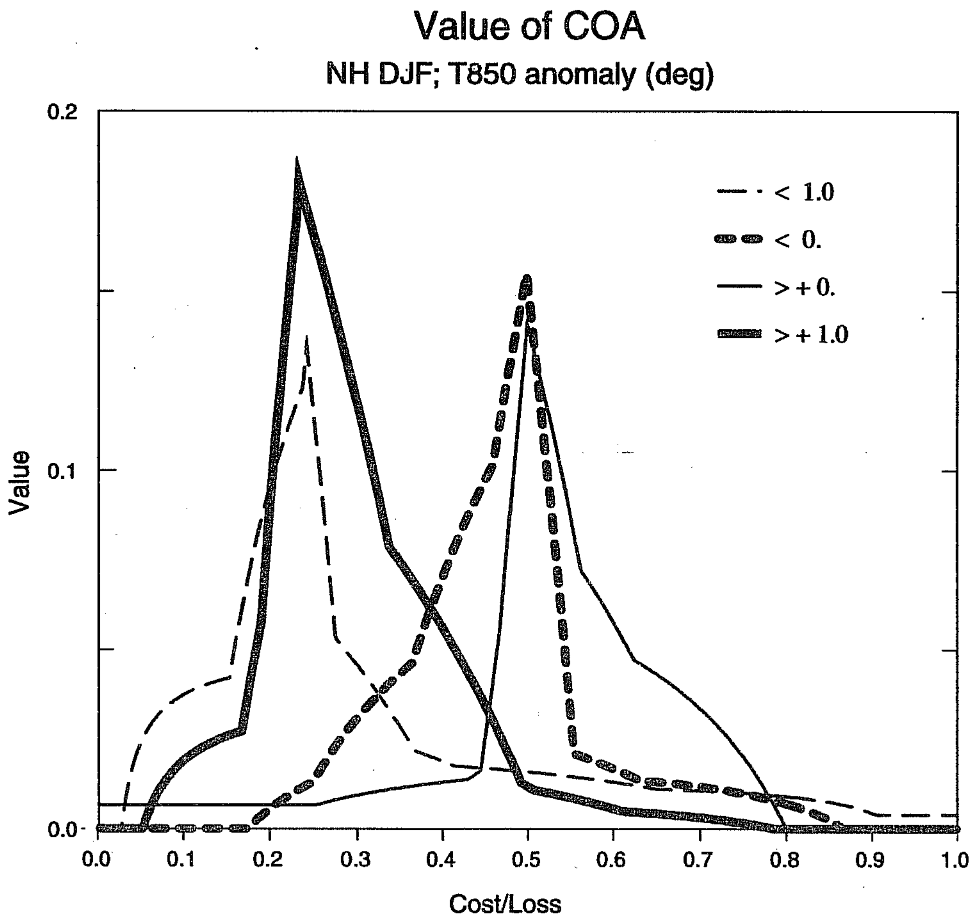

Fig 1: Value curves based on ECMWF coupled-model output from forecasts made over the 1990s, as a function of user cost-loss ratio. Value is normalised so that 0 represents no value over a knowledge of the climatological frequency of the event, 1 is the value associated with a perfect deterministic forecast. The events shown are based on 850 hPa temperature and taken over all northern hemisphere grid point.