# Review of recent developments in seasonal forecasting of rainfall

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## Abstract

General circulation models generally provide underestimates of the seasonal forecastability of the atmosphere as a result of their inability to simulate adequately the atmospheric response to sea-surface temperature anomalies and because of their exaggeration of the effects of the chaotic behaviour of the atmosphere. As a result, statistical forecast models will continue to provide a useful supplement to the dynamic models, although there is a need for the statistical models to capture explicitly the non-linear behaviour of the ocean-atmosphere system. Of concern, however, is the observation that forecast skill in many areas of the world appears to have decreased since the late 1980s. Careful validation of this possibility is required for South Africa.

## Introduction

Because of the high degree of inter-annual rainfall variability in the Southern African region, skilful seasonal forecasts could greatly assist in planning policies for the amelioration of drought and flood conditions (Vogel, 1994). Partly in response to the devastating effects of the 1991/92 drought in Southern Africa, the South African Weather Bureau (SAWB) and a number of research groups in the South African universities have begun to release seasonal rainfall forecasts in the last few years (Mason et al., 1996). In October 1994, at the initiative of the SAWB, the South African Long-lead Forecast Forum (SALFF) was founded with the purpose of developing and co-ordinating the seasonal forecasting capabilities of the country. Mason et al. (1996) presented a review of the prospects for the further development of the capabilities for Southern Africa, concluding that there are good prospects for improving seasonal forecast skill and lead-times over most of the region. Much of the predictability of rainfall over Southern Africa is attributable to variability in the tropical atmospheric circulation, which responds directly to boundary forcing such as sea-surface temperature anomalies, including El Niño events. As a result, highest forecast skills are obtainable for the peak rainfall months December to February over the summer rainfall region. In this review, an update of international developments in seasonal forecasting since the Mason et al. (1996) review is presented and implications for forecasting capabilities in Southern Africa are discussed.

## Developments in seasonal forecasting using statistical methods

### Estimating the potential predictability of the atmosphere

The potential for predicting atmospheric variability beyond the two-week limit of numerical weather forecasting arises for two reasons. Firstly, certain features of the large-scale components of the atmosphere may have greater predictability than the synoptic conditions, which tend to display a higher degree of chaotic behaviour. The large-scale atmospheric components, such as westerly waves, may have some influence on the probability of individual synoptic weather patterns, thus making probabilistic forecasts of general conditions beyond two weeks possible. A second source of potential predictability of the atmosphere comes from the influence of more slowly evolving boundary conditions such as sea-surface temperatures, snow cover and soil moisture. These boundary conditions can have an important influence on the overlying atmospheric circulation.

Estimates of the potential predictability of the atmosphere have been made using general circulation model (GCM) output. The atmospheric modelling intercomparison project (AMIP) has provided an opportunity for estimating potential predictability from boundary-layer forcing, specifically from sea-surface temperatures. The project involved the GCM-simulation of atmospheric variability for the 10-year period 1979 to 1988 using observed sea-surface temperatures for the same period. The simulated ensemble variability for the AMIP period could then be compared with the ensemble variability of control runs, using unvarying climatological sea-surface temperatures (Dix and Hunt, 1995). If sea-surface temperatures do provide a source of atmospheric predictability then the correlations between individual GCM AMIP experiments, differing only in their initial conditions, should be significant. In Fig. 1 the average correlations between three ensembles are represented for the CSIRO nine-level GCM (Dix and Hunt, 1995). The results confirm that most predictability lies within 20° of the equator, and particularly in areas where rainfall is predominantly from a single well-organised quasi-permanent circulation system, such as the Inter-Tropical Convergence Zone (Hastenrath, 1995). Tropical sea-surface temperatures are the main source of predictability, even within the mid-latitudes (Lau and Nath, 1994). Unfortunately, even within the tropics, estimated potential predictability is disproportionately small over the land area (Dix and Hunt, 1995) (Fig. 1), including over Southern Africa (Harrison, 1996).

Sea-surface temperatures are generally prescribed in general circulation models to provide forecasts of the state of the atmosphere with lead-times of about one to five or six months. For lead-times of about two weeks to one month, extended-range numerical weather forecasts are provided (Palmer and Anderson, 1994), which are based on attempts to model the evolution of the

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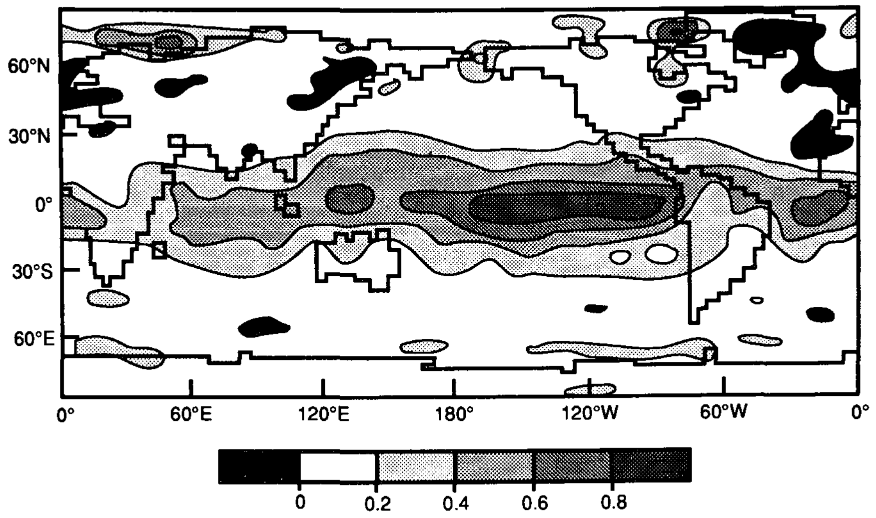

***Figure 1***
*Average correlations of time series of monthly rainfall anomalies at each grid point between three CSIRO 9-level model AMIP runs. The three runs differ only in their initial conditions (after Dix and Hunt, 1995). High correlations indicate areas with a reproducible atmospheric response to sea-surface temperature forcing.*

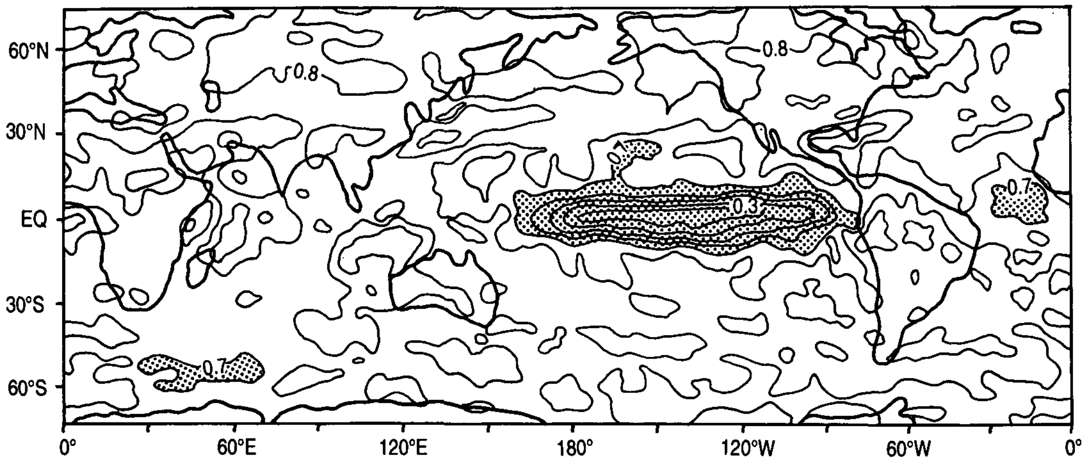

***Figure 2***
*Time-averaged ratios of nine-member ensemble variability to the model's climatological variability for December-February precipitation (after Stern and Miyakoda, 1995). Areas with ratios of less than 0.7 are shaded. Low values of the ratio indicate areas with a reproducible atmospheric response from different initial conditions.*

atmosphere from one regime to the next, given the initial conditions of the atmosphere (Shukla, 1981; Legras and Ghil, 1985; Roads, 1985; Murphy, 1988; Tribbia and Baumhefner, 1988). The initial conditions are important because of the chaotic nature of the atmosphere, especially in the mid-latitudes (Dix and Hunt, 1995; Peng et al., 1995). Predictability from initial conditions can be identified by the ratio of ensemble variability to climatological seasonal variability (a normalised measure of spread of ensemble forecasts) (Stern and Miyakoda, 1995). Smaller values of the ratio give an indication of high levels of predictability since the consensus among the ensemble members is relatively good. Again most predictability lies within 20° of the equator, with some occasional potential predictability in the extra-tropics (Stern and Miyakoda, 1995) (Fig. 2).

Until recently, the effects of initial conditions have not been considered of great importance in seasonal forecasting. The initial conditions were thought to become unimportant after a few weeks when the influence of boundary conditions on preferred weather regimes was supposed to become dominant. In seasonal forecasting a set of ensemble forecasts is usually obtained by producing separate forecasts with slightly different initial conditions and the ensemble mean or probability density function of the ensemble members is then calculated. By obtaining additional ensemble sets for which the initial conditions are fundamentally different compared to those of the other sets, the persistence of the effects of initial conditions can be tested. It has been shown that differences in the ensemble means become statistically insignificant only after a few months (Barnett, 1995), suggesting that seasonal forecasts with lead-times of even up to three months may need to take account of the current state of the atmosphere.

### Problems with general circulation model seasonal predictions

Statistical forecasting methods often seem to perform better than GCM estimates of maximum potential skill, but because of systematic errors the GCMs are probably underestimating predictability. The predictability of the atmosphere is underestimated partly because of inadequate/incorrect simulated responses to sea-surface temperature anomalies (Latif et al., 1994). For example, most models simulated a weak atmospheric response to the 1982-1983 El Niño-Southern Oscillation (ENSO) event in the AMIP experiment (Smith, 1995), including in the Southern African region (Joubert, 1996), because the modelled tropical convection response to positive sea-surface temperature anomalies is generally too weak (Mo and Wang, 1995).

Systematic model errors result in an exaggeration of the importance of atmospheric chaos (Dix and Hunt, 1995), which again is responsible for underestimates of potential predictability. Ensemble forecasting to some extent resolves this problem because the ensemble reduces the influence of the model's random internal variability on the forecast and indicates the climate state to which the atmosphere has the greatest probability of tending toward (Palmer and Anderson, 1994; Kumar and Hoerling, 1995). Ensemble forecasting does not, however, account for the possibility that model systematic errors are regime dependent. The time-mean model errors for warm and cold ENSO events have been shown to be different and to differ from the time-mean error of a 10-year control integration (Mo and Wang, 1995). The correction of a forecast by adjusting for time-mean model systematic errors is therefore invalid. Ensemble forecasts produced using different forecasting models, possibly with different forecast skills, have been recommended to reduce the problem of model systematic errors (Vislocky and Fritsch, 1995). The development of a number of separate GCM seasonal forecasting capabilities within southern Africa should therefore be encouraged. In addition, GCM forecasts should be used in conjunction with statistical methods at least until the dynamic models can respond more realistically to sea-surface temperature anomalies.

## Developments in seasonal forecasting using statistical methods

### Effects of non-linearity on forecast skill

Despite the inherent problems with GCM seasonal forecasts, in theory, they should provide higher forecast skills than statistical methods because of the non-linearity of the ocean atmosphere system (Zhang and McPhaden, 1995) and because of the importance of soil-moisture and other boundary layer feedbacks. Both the non-linearity of the climate system and the feedback processes can be explicitly captured by the dynamical models (Smith, 1995). Non-linear interactions between the atmosphere and the oceans are exceptionally difficult to reproduce in a statistical model. One potential solution is to use neural networks, which are, in effect, highly complex non-linear regression models. A neural network model has been used for hindcasting December-February rainfall over the Highveld of South Africa (Hastenrath et al., 1995). Predictors used were the Southern Oscillation Index, the Quasi-biennial Oscillation, Indian Ocean equatorial winds and sea-surface temperatures, most of which have been tested using simpler statistical models with linear constraints. The neural network model was found to produce skill levels that are considerably higher than those obtainable from linear regression techniques (62 per cent of the variance compared to 30 per cent) and linear discriminant analysis methods with identical predictors (cf. Allen and Le Marshall, 1994; Sansom, 1995). The results highlight the importance of using non-linear statistical methods when forecasting Southern African rainfall. Current statistical methodologies used by members of the SALFF are all linear, except for the quadratic discriminant analysis model used by the Climatology Research Group, University of the Witwatersrand, which provides only a simple departure from the linearity constraint (Mason, 1995a).

### The importance of optimal time-averaging

The need to identify the optimal averaging period for which seasonal forecasts are produced has been emphasised (Barnston, 1994). In the short term, the internal variability of the atmosphere is relatively large and so, on time scales of less than about one month, the influence of boundary conditions is unimportant. The averaging of forecasts over longer periods improves predictability because of the decreased influence of internal variability associated with synoptic events or relatively high-frequency events such as the Madden-Julian Oscillation (Barnston, 1994). Time averaging aims to minimise the influence of individual synoptic events on the statistics of the forecast period. At the other extreme, predictive skill can decrease if the averaging period is too long because of the seasonal dependence of the atmospheric response to boundary-layer forcing (Kumar and Hoerling, 1995). In Southern Africa, the only attention that has been paid to the problem of defining optimal forecast periods is to divide the summer season into the early, mainly temperate half and the later, tropical half. A more careful definition of optimal forecast periods may be warranted.

### Two-tiered forecasting

It is evident from Fig. 1 that globally the highest predictability is over the equatorial Pacific Ocean and reflects the high predictability of the ENSO phenomenon. Predictability is high throughout the tropics largely because of the direct response of the tropical atmosphere to sea-surface temperature forcing. A two-tiered forecasting approach has been proposed to take full advantage of the predictability obtainable from sea temperatures in the tropics: forecasted sea-surface temperatures are used as an input to the atmospheric forecasting model (Bengtsson et al., 1993). In particular, the method allows use to be made of the high forecast skill of Pacific Ocean sea temperatures and potentially of forecasts of sea-surface temperatures in the Atlantic and Indian oceans (Latif and Barnett, 1995). Currently, most seasonal forecasting models (dynamic and statistical) make use of real-time or near real-time data only. Rainfall over Southern Africa shows strong associations with sea-surface temperatures in a number of areas (Mason, 1995b), most notably the equatorial Indian Ocean (Jury and Pathack, 1991), which the operational forecasts are largely based upon (Mason et al., 1996). Some progress has been made by the Research Group for Statistical Climate Studies at the SAWB in initial attempts to forecast Indian Ocean sea-surface temperatures using statistical methods (Landman, 1995). Further research to forecast sea-surface temperatures around southern Africa would be beneficial, but requires an improved understanding of the complexities of ocean-atmosphere interaction in the region.

## Seasonal forecasting of the atmosphere in temperate latitudes

The importance of initial conditions is of greatest significance in the mid-latitudes where the atmosphere does not always respond in a consistent manner to boundary-layer forcing (Dix and Hunt, 1995; Peng et al., 1995). As a result, there is apparently no statistically significant extra-tropical response in the northern hemisphere to ENSO events, except in the zonal flow of the subtropics (Harzallah and Sadourny, 1995; Hoerling et al., 1995; cf. Graham and Barnett, 1995). However, strengthened zonal flows are evident in individual ENSO years, resulting in large amplitude stationary wave anomalies, that are generally long-lived, and that are typical of the Pacific-North America (PNA) pattern (Hoerling et al., 1995). Selective interaction with ENSO events also occurs within the tropics, for example with the Asian monsoon (Annamalai, 1995; Webster, 1995), but is generally more evident in the temperate atmosphere. The high degree of internal temperate atmospheric variability is an additional reason why statistically significant mid-latitude responses to boundary-layer forcing are difficult to identify. Climate extremes can occur even in the absence of forcing, and general circulation models have successfully simulated extremes from climatological sea-surface temperatures (Barnett, 1995). For example, the PNA pattern can occur even in the absence of ENSO forcing (Deser and Blackmon, 1995; Harzallah and Sadourny, 1995).

Despite the chaotic nature of the mid-latitude atmosphere, some statistical predictability, with lead-times of up to 6 months, has been claimed for the Pacific-North America sector. Forecast skill is greatest in January to April and is largely a result of tropical sea-surface temperature forcing in the Pacific Ocean (Barnston, 1994; Graham and Barnett, 1995). The fact that ENSO events tend to reach full maturity during the boreal winter is partly responsible for the seasonal dependence of ENSO-related forecast skill in the northern hemisphere mid-latitudes. Of greater importance, however, is the fact that the northern Hadley cell overlies the tropical sea-surface temperature anomalies at this time of year. A secondary predictability maximum is evident for the warm season and is partly a result of the atmospheric response to long-lived episodes of sea-surface temperature anomalies in the tropical oceans around the world (Barnston, 1994). In addition, weaker westerly winds during the summer help to prolong positive sea-surface temperature anomalies because of a decrease in evaporative cooling and less turbulent mixing with cooler subsurface waters (Webster, 1982). The prolongation of sea-surface temperature anomalies in summer contributes to the secondary predictability maximum.

Although the atmosphere in the mid-latitudes can respond with large anomalies to the boundary-layer, the signal to noise ratio is weak and the response is not always predictable. Standard methods of analysis of observational data, such as correlation or composite analysis, and of general circulation model sensitivity test output, such as comparison of means, are therefore unlikely to identify statistically significant responses in the mid-latitude atmosphere to sea-surface temperature anomalies. These results have important implications for seasonal forecasting in Southern Africa. Although some efforts have been made to identify a mid-latitude response to tropical sea-surface temperature anomalies such as El Niño events (see Tyson, 1986 for a review of early research; Jury et al., 1994), the statistical significance will inevitably be difficult to prove and it should be born in mind that more than one mode of response may be detectable. Further, a response in the southern hemisphere is likely to be strongest when the southern Hadley cell overlies the tropical sea-surface temperature anomalies, which occurs during the austral winter and at a time when El Niño has not usually reached maturity. A southern hemispheric response with similar significance to the PNA pattern is therefore unlikely and would occur during the winter months when most of the Southern African region experiences dry conditions. Although significant correlations have been identified between winter rainfall over South Africa and the Southern Oscillation Index (Mason and Lindesay, 1993), the rainfall data are highly skewed. Results based on Pearson's product moment correlation coefficient must therefore be approached with caution. Nevertheless, there may be some useful potential for predicting wintertime temperatures and rainfall over the winter and all-seasons rainfall regions. Three-month temperature forecasts have been released by the South African Weather Bureau Research since March 1996 (South African Weather Bureau, 1996), but it is too early to give an impression of the operational forecast skill.

## Inter-decadal changes in predictability

A decrease in the performance of statistical and dynamical seasonal forecasting models for the 1990s has been observed (Hastenrath, 1995). For example, forecasts of North Atlantic storm frequencies were exceptionally accurate up until 1989, but have since deteriorated. A decrease in the success of Indian monsoon forecasts since the 1980s has also been observed, as well as a worsening of the performance of the Cane-Zebiak model. The recent apparent decrease in predictability is partly the result of inter-decadal variability in the ocean-atmosphere system (Graham, 1994; Allan et al., 1995; Wang, 1995), but also emphasises the importance of identifying robust predictors (Singh et al., 1995) and of the need for careful cross-validation of forecast methodologies. The rather disappointing performance of operational forecasts produced for Southern Africa during the 1990s, compared to hindcast skills obtained over training periods, may be a reflection of the decrease in skill observed elsewhere.

## Summary and recommendations

Increasingly, general circulation models are being used to produce operational or experimental seasonal and extended-range weather forecasts. These dynamic models, however, generally suggest that there is only weak predictability of the atmosphere. Normalised measures of ensemble variability suggest that, although initial conditions provide some predictability of the atmosphere with lead-times of about two weeks to beyond one month, most of this predictability is for the tropical atmosphere. Similar sensitivity experiments using general circulation models again provide disappointing estimates of atmospheric predictability from sea-surface temperatures with lead-times of a few months. The results suggest that only limited success can be achieved in the development of seasonal and extended-range forecasting capabilities. There are, however, a number of limitations in the use of dynamic models. The most severe restriction is that model limitations and systematic errors result in underestimations of the predictability of the ocean-atmosphere system, especially outside of the tropics. Ensemble averaging resolves this over-chaotic behaviour of the models only to an extent. An assessment of the potential predictability of the atmosphere as estimated by the NMC and COLA models, used in operational one-month forecasts released by the South African Weather Bureau, would be useful for an assessment of the confidence that can be placed in the forecasts.

Because of the poor performance of general circulation models in forecasting the atmosphere with lead-times of more than two weeks, there is a continued need for statistical forecasts. There are, however, some severe limitations in the statistical models currently used to provide seasonal forecasts of rainfall over Southern Africa. The most severe restriction is the failure to take adequate account of the non-linear behaviour of the ocean-atmosphere system. It has been shown that significant improvements in forecast skill for Southern Africa are obtainable when non-linear models have been used.

International research has indicated the need for optimal time-averaging when producing seasonal forecasts. There is a trade-off between exaggerating the influence of individual synoptic systems in the shorter time-averaged periods and encountering problems of the seasonal dependence of rainfall predictors in longer periods. Longer lead-times than those currently used may be obtainable for summer rainfall in the second half of the season when the tropical atmosphere generally has a stronger influence. At other times of the year, improved skill may be obtained by reducing the period of the forecast. It may be additionally possible to improve forecast skill and/or lead-times by using forecasted rather than observed sea-surface temperatures in the models currently used.

Probably of greatest concern is the observation that seasonal forecast skill in many areas of the world appears to have decreased since about the beginning of the decade. It is quite possible that a similar trend is evident for South Africa. Careful validation of this possibility is required and an update of the training periods for the statistical forecasts currently produced by SALFF members would be necessary. It is possible that changes in the global atmospheric circulation have affected the forecast skill obtainable from currently used predictors; improvements in skill may be obtainable if the forecast models are updated.

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