# The potential for long-range prediction of seasonal mean temperature in Australia

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**The contribution of synoptic-scale weather to the interannual variability of seasonal mean temperature has been estimated, for 19 Australian stations, using an autoregressive modelling approach. It is concluded that synoptic-scale fluctuations can contribute more than 50 per cent of the observed variance of the seasonal means in some areas. The contribution is lower in the tropics and in the period June-November, than in the extra-tropics and for the rest of the year. The results are similar to those obtained using a spectral analysis approach. It is suggested that in the areas and seasons where the synoptic events play a major role in determining the interannual variability, accurate long-range predicition of seasonal mean temperature is unlikely to eventuate. In the other regions and seasons, where the synoptic events play only a minor role in determining the interannual variability, long-range prediction could be feasible.**

## Introduction

Proponents of long-range weather prediction postulate, either explicitly or implicitly, that fluctuations of weather elements arise from two approximately separable components (Madden 1981). The first component results from synoptic-scale weather disturbances. It is believed that there is a practical limit of about two weeks to the deterministic predictability of the weather associated with this synoptic scale, at least in middle latitudes (Smagorinsky 1969). Thus on the time scales of interest in long-range forecasting, only the second component of weather fluctuations is potentially predictable. This latter component (which involves fluctuations on a much longer time-scale than the synoptic component) is generally attributed to external forcing of the atmosphere by, for instance, sea surface temperature anomalies or variations in surface albedo. Some portion of these longer period fluctuations may also arise from non-linear interactions in the atmosphere, even in the absence of external forcings. This long period component of atmospheric variability may be predictable at long lead times but it is generally swamped by the unpredictable (at long lead times) but larger amplitude synoptic variability, if data are examined on a day-to-day basis. We therefore need to filter out the synoptic component of atmospheric variability, thereby leaving only the potentially predictable portion of the variability. This filtering is generally performed by taking monthly or seasonal (or longer) averages of the element in which we are interested. Long-range forecasting, for this reason, generally refers to prediction of monthly or seasonal (or longer) averages.

Unfortunately, such averaging does not completely remove the variability associated with synoptic events. The variability associated with these synoptic events contributes to the interannual variability of monthly or seasonal means. If daily meteorological observations could be regarded as being independent and having a variance of $\sigma^2$, then it is a basic statistical result that 90-day means of the observations would have a variance of $\sigma^2/90$, in the absence of any interannual variations resulting from changes in boundary conditions. In fact, the daily observations are not independent and the variance of the 90-day means will be larger than $\sigma^2/90$. This variance is commonly called 'climate noise'. Nicholls (1980) suggested that a first step in a search for long-range predictability should entail an attempt to separate the proportion of the variability of monthly or seasonal averages arising from synoptic events, from the remainder of the variability on these time-scales. If it is found that the synoptic contribution to the variability is large, then there seems little possibility that long-range forecasting will be feasible. On the other hand, if this contribution is small, then we can conclude that external forcings or long-period non-linear interactions are the dominant influence on the monthly or seasonal averages and the potential for long-range prediction exists. How then can we calculate the variability of time-averages of synoptic events?

Several authors (Jones 1975, 1976; Leith 1973; Madden 1979, 1981) have proposed that the variance of time-averages of an atmospheric variable be estimated by the use of time series models. If an adequate model, taking into account the autocorrelation of the variable, can be identified then an estimate of the variance of time-averages of the variable can be obtained from only a relatively short time-series of the variable. Some authors (Leith 1973; Madden 1979) have assumed that atmospheric time-series can be adequately represented by Markov (i.e. first-order autoregressive) processes. Strauss and Halem (1981) suggested that higher order models were required to adequately fit atmospheric data. Katz (1982) describes a method for fitting higher order autoregressive models, as well as first-order and zero-order (i.e. uncorrelated) models to time-series, along with an automatic model selection criterion to choose the appropriate order. This study uses the method described by Katz, with one slight change, to estimate the variance of seasonal averages of mean daily temperature arising from the effect of synoptic rather than long-period variations in temperature, for a number of Australian stations.

An alternative approach to the estimation of the variances of the time-averages could have been to use the spectral analysis technique adopted by Madden (1976), Madden and Shea (1978) and Nicholls (1981). Katz (1982) discussed the merits of the two approaches and concluded that they should result in estimates of variances that are in close agreement. Katz recommended the use of the autoregressive modelling approach because it required less subjective judgment than the spectral approach.

Once the variance of the seasonal averages of daily mean temperature caused by the synoptic variations has been estimated, it can be compared with the observed variance of seasonal averages (which can be simply calculated from a time-series of a number of years of data). In this paper the ratio of these two variance estimates is examined for a number of Australian stations. Seasonal variations of this ratio are also examined. Throughout the remainder of the paper the observed interannual variance of the seasonal mean temperature is denoted by $\sigma^2_{obs,}$ while $\sigma^2_n$ represents the part of this variance arising from synoptic fluctuations. The variability of the seasonal means **not** caused by short-period synoptic fluctuations is therefore $\sigma^2_{obs}$-$\sigma^2_n$.

Madden (1976) suggested that only in areas where the ratio $\sigma^2_{obs}/\sigma^2_n$ is large should there be much potential for long-range prediction. Several authors (Madden 1976; Madden and Shea 1978; Barnett 1981; Charney and Shukla 1981; Nicholls 1981) have suggested that this ratio shows spatial and seasonal variations. Charney and Shukla (1981) suggested that interannual variations in the climate at low latitudes might show greater potential of long-range predictability, i.e. that the ratio $\sigma^2_{obs}/\sigma^2_n$ is larger in low latitudes. They found some evidence to support their hypothesis in the work of Madden (1976) although Madden's study did not extend to tropical latitudes. The principal aim of the present study is to examine the seasonal and spatial variations in the ratio $\sigma^2_{obs}/\sigma^2_n$ and to test the hypothesis of Charney and Shukla (1981). The use of stations ranging in latitude from about 10°S to 43°S should provide data to enable the testing of this hypothesis.

The method used to calculate the ratio $\sigma^2_{obs}/\sigma^2_n$ is briefly described in the next section (further details are available in Katz 1982). The following section then describes and discusses the results.

## Method

Katz (1982) describes a procedure for making statistical inferences about differences between means from the output of general circulation models. Two steps are required in his procedure: first, the appropriate order of the autoregressive process is selected to fit the time-series of data, and secondly, based on the autoregressive model chosen, an expression for the variance of the time averages of the time-series is derived. Although Katz noted that this procedure could be used on time-series of atmospheric data to estimate the variance of time-means arising from synoptic, daily weather fluctuations, he concentrated on its application to climate model output, and only fitted the parametric model to winter and summer time-series. In the case examined in the present paper, real observed atmospheric data are fitted to the model and data from all four seasons are used. In spring and autumn especially, strong trends associated with the annual cycle occur in the time-series of daily temperature; these need to be removed before the time-series model is fitted.

Daily mean temperatures for 1979-80, at the stations listed in Table 1, for each of four seasons, each of 90 days, were fitted to the time-series model using the procedure described by Katz. The daily mean temperature was calculated by averaging the daily maximum and minimum temperatures. The annual cycle in the data was first removed by calculating long-period (25 year) averages of temperature for each station for each day of the year and then subtracting this long-period average from the appropriate day in the 1979-80 data. Thus if $T_{syd}$ is the observation of daily mean temperature at station s, in year y and day d, then the annual cycle was removed by calculating

$$T'_{syd} = T_{syd} - \frac{\sum_{y=1}^{m} T_{syd}}{m}$$

where m is the number of years (25) of data used in calculating the long-period average. The values of the daily temperature anomalies in 1979-80 ($T'_{syd}$) then replace the initial daily mean temperatures ($T_{syd}$) in the rest of the calculations.

For generality, and to ensure conformity between this paper and Katz (1982), $T'_{syd}$ has been replaced

**Table 1. Stations used in the study with estimated ratio of observed variance ($\hat{\sigma}^2_{obs}$) of seasonal mean temperature to the variance attributed to climate noise ($\hat{\sigma}^2_n$), for each season.**

| Station | Lat. (°S) | Long. (°E) | Ratio for Each Season Mar-May | Jun-Jul | Sep-Nov | Dec-Feb |
|---|---|---|---|---|---|---|
| Thursday Is. | 11 | 142 | 8.3 | 14.2 | 16.8 | 3.0 |
| Darwin | 12 | 131 | 5.9 | 16.0 | 2.6 | 5.3 |
| Cairns | 17 | 146 | 5.9 | 9.1 | 4.8 | 1.7 |
| Tennant Ck | 20 | 134 | 2.4 | 7.7 | 2.9 | 6.7 |
| Pt Hedland | 20 | 119 | 1.6 | 1.1 | 2.0 | 1.3 |
| Alice Springs | 24 | 134 | 1.7 | 1.6 | 1.5 | 4.5 |
| Giles | 25 | 128 | 1.4 | 1.1 | 7.7 | 2.7 |
| Birdsville | 26 | 139 | 2.0 | 2.0 | 3.6 | 1.8 |
| Meekathara | 27 | 119 | 2.4 | 1.3 | 1.6 | 1.1 |
| Brisbane | 28 | 153 | 2.2 | 2.2 | 2.8 | 3.2 |
| Geraldton | 29 | 115 | 1.6 | 4.8 | 1.1 | 1.1 |
| Kalgoorlie | 31 | 121 | 2.9 | 1.8 | 3.2 | 2.6 |
| Forrest | 31 | 128 | 1.2 | 2.1 | 3.2 | 3.8 |
| Perth | 32 | 116 | 1.5 | 6.7 | 2.4 | 1.7 |
| Ceduna | 32 | 134 | 1.3 | 3.4 | 2.5 | 2.6 |
| Sydney | 34 | 151 | 2.1 | 1.8 | 2.9 | 5.9 |
| Mildura | 34 | 142 | 1.3 | 1.7 | 3.3 | 1.3 |
| Melbourne | 38 | 145 | 2.2 | 2.3 | 3.4 | 2.2 |
| Launceston | 42 | 147 | 2.0 | 1.4 | 2.6 | 2.0 |

by $\{X:t = 1, 2, \ldots\}$ (representing a realisation of a stochastic process) in what follows. This stochastic process is assumed to be stationary with unknown population mean ($\mu$) and variance ($\sigma^2$). Four series of 90 successive days of daily mean temperature anomalies ($T'_{syd}$), at each station, starting on 1 March, 1 June, 1 September, and 1 December (referred to as autumn, winter, spring and summer, respectively) in 1979 were fitted to the time-series model. The following statistics were calculated for each time-series:

(a) The time average,

$$\overline{X} = n^{-1} \sum_{t=1}^{n} X_t$$

(b) The sample autocovariances,

$$C_k = n^{-1} \sum_{t=k+1}^{n} (X_{t-k} - \overline{X})(X_t - \overline{X})$$
$$k = 0, 1 \ldots p_u$$

It is assumed that the time-series can be represented as an autoregressive process of some unknown order p (in practice an upper bound of $p_u = 5$ has been assumed; it is unlikely that higher orders would be required). A p'th order autoregressive process, denoted AR(p), can be expressed as

$$\sum_{k=o}^{p} \phi_k (X_{t-k} - \mu) = a_t, \qquad t = p + 1, p + 2 \ldots$$

with $\phi_o = 1$ and the other autoregression coefficients to be estimated. The $a_t$'s constitute a white noise process; i.e. they are uncorrelated random variables with zero mean and variance $\sigma_a^2$.

The autoregression coefficients and the white noise variance can be estimated with the Yule-Walker recursive method (Box and Jenkins 1976, p. 82). A Bayesian information criterion (Schwarz 1978) is used to automatically select the appropriate order p. This procedure is a consistent estimator of the order of an autoregressive process (Hannan 1980); i.e. the probability of selecting the correct order converges to one as the sample size n tends to infinity, assuming that the process really is autoregressive of a finite order. A number of other criteria for selecting the model order have been suggested (e.g. Hannan and Quinn 1979).

Once the order p is chosen and the autoregression coefficients ($\phi_k$, $k = 1, 2 \ldots p$) and white noise variances ($\sigma_a^2$) are estimated, the variance ($\sigma_n^2$) of the time mean of the time-series can be estimated as

$$\hat{\sigma}_n^2 = \frac{\sigma_a^2}{\left[\sum_{k=o}^{p} \phi_k\right]^2}$$

for large n.

With the procedure outlined above, and described in more detail by Katz (1982), $\hat{\sigma}_n^2$ was calculated from the 1979-80 data for the 19 stations for each of the four 90-day seasons. Then, from 25-32 years data were used to calculate the observed variance ($\hat{\sigma}^2_{obs}$) of the seasonal mean temperature for each station and season. The ratio $\hat{\sigma}^2_{obs}/\hat{\sigma}^2_n$ was then calculated for each season and station. The calculated values of $\sigma^2_n$ could be biased towards low values due to overfitting of the data (Miller, personal communication). If so the ratio $\hat{\sigma}^2_{obs}/\hat{\sigma}^2_n$ would be biased towards high values, suggesting a greater potential for long-range prediction than actually exists. The spatial and seasonal variations in the ratio will probably not be substantially affected by the possible existence of this bias.

## Results

Analyses of the ratio $\hat{\sigma}^2_{obs}/\hat{\sigma}^2_n$, calculated for the four seasons and 19 stations, are listed in Table 1. The larger the ratio in Table 1, the smaller is the contribution of the synoptic, unpredictable (at long lead times) scales, and thus the greater is the potential for long-range prediction.

It is clear, from Table 1, that synoptic-scale weather fluctuations can make a major contribution to the interannual variability of seasonal mean temperature. In each season, there are stations where the ratio is less than 2.0; at these stations at least half of the observed variances of seasonal mean temperature is the result of daily weather fluctuations, and does not represent external forcings or long-period fluctuations. The inherent unpredictability of the synoptic scale at long lead times thus places a limit on the accuracy obtainable by long-range forecasts of seasonal mean temperature. Where the ratio is less than 2.0, no more than 50 per cent of the variance of the seasonal mean temperature could be accounted for by even a 'perfect' long-range forecast system, i.e. a system that can accurately predict that part of the interannual variability not due to synoptic-scale weather fluctuations.

Considerable spatial variation is evident in Table 1. Stations with large values of the ratio (> 4.0) are almost completely confined to the tropics. In each season, at least two of the five stations north of 20°S have $\hat{\sigma}^2_{obs}/\hat{\sigma}^2_n > 4.0$ while south of this latitude only a few stations show high values. Most of the stations with small values of the ratio (< 2.0) are located south of 20°S. Thus Table 1 provides evidence of a higher potential for long-range predictability of seasonal mean temperature in the tropics. The same result was reported by Nicholls (1981) who used the spectral method to examine the potential for the long-range predictability of monthly mean temperature and pressure at two Australian stations, one in the tropics (Darwin) and the other situated on the southern coast (Adelaide). The monthly mean data at Darwin were affected by synoptic events to a much smaller degree than at Adelaide. As was noted earlier, Charney and Shukla (1981) suggested that low latitudes would show lower values of the ratio $\hat{\sigma}^2_{obs}/\hat{\sigma}^2_n$ than would high latitudes.

Seasonal variations in $\hat{\sigma}^2_{obs}/\hat{\sigma}^2_n$ can also be found in Table 1. For instance September-November has the fewest stations with a ratio less than 2.0, while June-August has the largest number of stations where the ratio exceeds 6.0. Thus these two seasons are less affected by synoptic-scale contributions to the interannual fluctuations of seasonal mean temperature, and therefore show greater potential for long-range prediction. By contrast, the other two seasons have many stations where the ratio is less than 2.0 and where the ratio is large. The seasonal variation is clearest in the tropics where very large values (> 12.0) of the ratio occur in June-August. Again, a similar seasonal variation was reported by Nicholls (1981), with a very strong seasonal variation in $\hat{\sigma}^2_{obs}/\hat{\sigma}^2_n$ at the tropical station (Darwin). The months from May to October showed the greatest potential for long-range prediction, closely matching the results shown in Table 1. The seasonal variation in the values of the ratio reported by Nicholls (1981) at Adelaide, outside the tropics, was smaller, again coinciding with the result reported here.

## Concluding remarks

This paper has described the results of applying a parametric time-series model to daily mean temperature at 19 Australian stations to determine the contribution that synoptic-scale weather fluctuations makes to the interannual variability of seasonal mean temperature. It has been suggested that this contribution is unpredictable at long lead times (Madden 1981) so examination of the ratio of this contribution to the observed, total variance of seasonal mean temperature could identify areas where the potential for long-range prediction is high. The results of this examination are:

(a) In each season of the year, for large areas of Australia, synoptic-scale weather provides a major contribution to interannual variability of seasonal mean temperature.

(b) Synoptic-scale weather makes a higher contribution to interannual variability of seasonal mean temperature in the extra-tropics than in the tropics, supporting the suggestion made by Charney and Shukla (1981), that long-range prediction might be more feasible in the tropics.

(c) Seasonal variations are evident in the contribution of synoptic scale, with the southern hemisphere winter and spring showing the greatest potential for long-range prediction.

(d) The results obtained from the time-series modelling approach adopted here resemble the results from a spectrum approach applied by Nicholls (1981) to Australian data.

Nicholls (1980) suggested that estimation of the proportion of the interannual variability of climate arising from the unpredictable (at long lead times) synoptic-scale weather fluctuations should be the first step of an empirical search for long-range predictability. Only if such an estimate suggested that a considerable portion of the climate fluctuations were caused by external forcings or long-period non-linear interactions, would there be grounds for optimism that an empirical long-range forecast method might provide accurate forecasts. Earlier work (Nicholls 1981; Nicholls and Woodcock 1981; Nicholls et al. 1982) has demonstrated the feasibility of prediction of Australian seasonal rainfall, for some areas and seasons. It is interesting, as an aside, to note that the areas and seasons of demonstrated long-range predictability of rainfall generally coincide with the areas and seasons found, in the present study, to present the best chances of predictability of seasonal mean temperature. The prediction of Australian seasonal mean temperature has attracted much less attention than has the problem of long-range rainfall prediction. It would therefore be of interest to search for empirical long-range forecast techniques for seasonal mean temperature, to determine whether actual predictability is related to the magnitude of the ratio $\hat{\sigma}^2_{obs}/\hat{\sigma}^2_n$.

The conclusions of this paper are dependent on the assumption that, to a reasonable approximation, meteorological time-series can be treated as composed of two separable components: one component due to synoptic-scale weather disturbances and unpredictable at long lead times; the other due principally to changes in boundary conditions and potentially predictable at long lead times. Shukla (1983) has pointed out that the internal dynamics and boundary forcings cannot be completely separated, and that the estimates of climate noise derived from an assumption of separability must be somewhat suspect. Shukla suggested that for several reasons the estimates of predictability resulting from analyses such as the one described in the present paper could be overly-conservative, i.e. could suggest that long-term means of atmospheric variables were less potentially predictable than they really are. Madden (1983), while agreeing that the assumption of separability involves approximation and uncertainty, suggested that it was premature to conclude that the estimates of potential predictability were overly-conservative. Clearly, considerable work remains to be done to improve the estimates of potential long-range predictability. At this stage, however, the doubts raised by Shukla (1983) do not seem to contradict the conclusions of this paper.

The present study could be extended in a number of ways. Only 19 stations have been used in this study, too few to enable a complete picture of the seasonal and spatial variability of potential for long-range prediction to be gained. The use of mean maximum and mean minimum temperatures, rather than the mean daily temperature used here, could also provide further insight. Finally, further examination and clarification of the statistical techniques used to estimate potential predictability, for instance by examination of the possible effects of bias in model selection on the estimates of predictability, seems to be essential if we are to establish the limits to long-range predictability with confidence.

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