The estimated potential predictability of seasonal mean Australian surface temperature

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The seasonal mean of a climate variable is affected by processes with timescales from less than seasonal to interannual or longer. In this paper, the seasonal mean is conceptualised as consisting of intraseasonal and slowly varying (longer than a season) components. The slow component of the seasonal mean is related to slowly varying internal and external processes which are potentially predictable, and is therefore itself regarded as potentially predictable. An analysis of variance method, which separates the interannual variance of the seasonal mean of these components, is applied to Australian surface maximum and minimum temperature. The potential predictability is defined as the percentage of the interannual variance of the seasonal mean that is due to the slow component. Using data from the Australian Water Availability Project dataset for the period 1958–2007, it is found that there is high estimated potential predictability (over 50 per cent) for surface maximum and minimum temperature for northern Australia (north of 25°S) in most of the 12 three-month seasons. In contrast, there are regions of southern Australia (south of 25°S) with low estimated potential predictability (under 30 per cent) in many seasons. The results given here provide guidance for where and when long-range forecasts of seasonal mean temperature variables are most likely to be skilful.

Introduction

Forecasts of seasonal mean Australian surface temperature have been produced using both statistical (e.g. Jones 1998) and dynamical forecast schemes (e.g. Hudson et al. 2011). Changes in surface temperature are also often used to assess the impact of climate variability and climate change on Australian society and the environment (CSIRO 2007). It is well known that there is a strong relationship between the Southern Oscillation Index (SOI) and Australian surface temperature (e.g. Coughlan 1979, Halpert and Ropelewski 1992, Jones 1999, Jones and Trewin 2000a), and sea surface temperature (SST) has been successfully used as a predictor in statistical forecasts of Australian seasonal mean temperature (Fawcett et al. 2005). The skill of seasonal forecasts can be verified (e.g. Fawcett et al. 2005, Fawcett 2008, Fawcett and Stone 2010). However, an alternative question can be proposed: to what extent is the seasonal mean temperature potentially predictable for any given season and region?

Leith (1973) introduced the concept that the seasonal mean of a climate variable can be considered as a statistical random variable with ‘signal’ and ‘noise’ components. Within a three-month season, the ‘noise’ component changes on timescales from daily to intraseasonal. Thus, it is more likely to be related to meteorological phenomena that vary significantly within the season. The ‘noise’ component has been referred to as the intraseasonal component (e.g. Frederiksen and Zheng 2007). The ‘signal’ is regarded as being constant within the season. Therefore it is more likely to arise from slowly varying (season or longer) boundary or external forcings on the climate system, e.g. sea surface temperature (SST) variability, and from slowly varying internal atmospheric variability. The ‘signal’ can also be regarded as potentially predictable, as the related slowly varying external forcings and internal dynamics may themselves be predictable a season or more ahead (e.g. Madden 1976, Zheng et al. 2004). The ‘signal’ component has also been referred to as the slow component (e.g. Frederiksen and Zheng 2007).

Under this conceptual model, potential predictability can be defined as the fraction of the interannual variance of the seasonal mean remaining after the intraseasonal component has been removed (Madden 1976). A number of methods to estimate the interannual variance of the intraseasonal component have been developed using daily data (e.g. Madden 1976, Nicholls 1983, Zheng and Frederiksen 1999,
Feng et al. (2011) or monthly mean anomalies (e.g. Zheng et al. 2000, 2004). A review of these methods can be found in Frederiksen and Zheng (2007).

Nicholls (1983) estimated the potential predictability of Australian surface mean temperature using daily data from 19 stations and found spatial and seasonal variations in the potential predictability. Using monthly mean gridded data from the Jones and Trewin (2000b) dataset, Grainger et al. (2009) (hereinafter GFZ09) adapted the method of Zheng et al. (2004) to estimate the potential predictability of Australian surface maximum and minimum temperature in four seasons. The purpose of this paper is to extend the results of GFZ09. Using monthly mean gridded data from the updated Australian Water Availability Project (AWAP) dataset (Jones et al. 2009), the potential predictability of Australian surface maximum and minimum temperature will be estimated for all 12 three-month seasons. This will give an estimate of the upper limit to potential predictability over the annual cycle, and guidance on where and when long-range forecasts are more likely to be skillful.

Method

The Analysis of Variance method used to estimate the potential predictability of Australian surface temperature from monthly mean data is described in detail in GFZ09. Briefly, the monthly mean anomaly of a climate variable from monthly mean data is described in detail in GFZ09. The interannual variance of the intraseasonal component is the estimated interannual variance of

\[ \sigma_{yo}^2 \]

is the estimated interannual variance of

\[ \sigma_{y}^2 \]

= \sigma_{yo}^2 + \sigma_{yo}^2 + \sigma_{yo}^2 + 2(\sigma_{yo}\sigma_{yo} + \sigma_{yo}\sigma_{yo} + \sigma_{yo}\sigma_{yo}) \]

where \( E \) denotes the expectation value over all years, \( \sigma_{yo}^2 = \hat{V}(e_{yo}) \) is the estimated interannual variance of \( e_{yo} \) and \( \varphi_{mn} \) is the inter-monthly correlation between months \( m \) and \( n \), defined as

\[ \varphi_{mn} = \frac{\hat{V}(e_{yo}, e_{yo})}{\sigma_{yo}^2} m, n = 1, 2, 3, m \neq n \]

GFZ09 showed that for Australian surface temperature, the following constraints are appropriate:

\[ \sigma_{1} = \sigma_{2} - \beta, \quad \sigma_{2} = \sigma_{2} + \beta, \quad |\beta| < \sigma_{2}, \quad \ldots \]

\[ \varphi_{12} = \varphi_{23}, \quad \ldots \]

\[ \varphi_{13} = 0, \quad \ldots \]

Equations 5–7 respectively assume that the standard deviation of \( e_{yo} \) varies linearly by a slope \( \beta \) across a season; that the inter-monthly correlations are stationary within the season; and that the intraseasonal components are uncorrelated if they are more than one month apart. Applying these to Eqn 3 gives

\[ \hat{V}(e_{yo}) = \frac{1}{9} [\sigma_{yo}^2 (3 + 4\varphi_{12}) + 2\beta^2] \]

The estimation of \( \hat{V}(e_{yo}) \) from Eqn 8 using monthly moments is given in the Appendix.

From Eqns 1, 2 and 8, the variance of the slow component can be estimated as the residual of the total interannual variance after the variance of the intraseasonal component has been removed, i.e.

\[ \hat{V}(u_{io}) = \hat{V}(x_{yo}) - \hat{V}(e_{yo}), \]

The estimated potential predictability of \( x \) at a location for a given season is then defined as the percentage of the total variance that is due to the slow component, i.e.

\[ P = \frac{\hat{V}(u_{io})}{\hat{V}(x_{yo})} \times 100 \]

Results

Monthly mean surface maximum and minimum temperature were obtained from the AWAP 0.25° × 0.25° gridded dataset (Jones et al. 2009) for the period November 1957 to December 2007. Thus 50 years of data are available for each of the 12 three-month seasons. Monthly anomalies were calculated by subtracting the climatological mean, calculated over the entire 50-year period. The variance of each component was then estimated for all seasons.

It is useful to first summarise the annual cycle of seasonal-mean variability of Australian surface temperature. The total interannual variance (Eqn 2) of seasonal-mean Australian surface maximum and minimum temperature is shown in Figs 1 and 2 respectively. Seasons are denoted by their three-letter abbreviation (e.g. January–February–March is JFM). For surface maximum temperature (Fig. 1), the variance of the seasonal mean is largest over inland northern (north of 25°S) and Western Australia from DJF to MAM. Relative minima occur over much of Australia in MJJ and JJA. The variance increases over southern Australia (south of 25°S) from JAS to NDJ, especially over inland southeastern Australia east of 140°E.
Fig. 1. Total interannual variance ($^\circ$C$^2$) of seasonal mean AWAP surface maximum temperature from 1958–2007 for all 12 three-month seasons. Seasons are denoted by their three-letter abbreviation (e.g., January–February–March is JFM).
Fig. 2. As in Fig. 1, but for AWAP surface minimum temperature from 1958–2007.
The interannual variance of seasonal-mean surface minimum temperature has a different annual cycle, and is typically lower than for surface maximum temperature (Fig. 2). Over northern Australia, the largest variance is inland from MAM to JJA, and has a minimum in DJF. Over southern Australia, variances are generally higher for NDJ to AMJ than for the other half of the year. For both surface maximum and minimum temperature, the interannual variance generally decreases towards the coast. Jones and Trewin (2000b) found similar behaviour for monthly standard deviations that they attributed to the moderating effect of the ocean.

The estimated potential predictability (Eqn 10) of Australian surface maximum and minimum temperature is shown in Figs 3 and 4 respectively. For surface maximum temperature (Fig. 3) there is high potential predictability (over 50 per cent) over most of northern Australia from JFM to AMJ and in JJA, with little change near the coast. At the same time, there is low potential predictability (less than 30 per cent) over much of southern Australia, particularly in the southeast from JFM to MAM. Low values also occur in central Australia in MJJ. From JAS to SON, potential predictability over northern Australia is lower than earlier in the year, but generally higher than before over most of southern Australia. In NDJ and DJF, the potential predictibility is over 50 per cent along most of eastern Australia, but less than 30 per cent in regions in the west.

For surface minimum temperature, there is high potential predictability throughout the year over most of northern Australia (Fig. 4). The potential predictability has similar values to that estimated for surface maximum temperature, even though the total interannual variance is often lower, e.g. from DJF to FMA. Over southern Australia, the potential predictability is less than 30 per cent for much of the year. For example, over southeastern Australia potential predictability exceeds 50 per cent only in MAM, JAS and ASO, while over southwest Western Australia it exceeds 50 per cent in MAM, ASO, OND and NDJ.

Discussion and conclusions

In this paper, an analysis of variance method has been used to estimate the potential predictability of Australian surface maximum and minimum temperature for all 12 three-month seasons for the period 1958–2007 using the updated AWAP dataset. For both surface maximum and minimum temperature, it was found that there is high estimated potential predictability (over 50 per cent of the interannual variance of the seasonal mean) over northern Australia throughout most of the year. In contrast, there is low estimated potential predictability (less than 30 per cent) over southern Australia in many seasons. The results for DJF, MAM, JJA and SON are generally consistent with those found by earlier studies (Nicholls 1983, GFZ09, Feng et al. 2011).

Although the estimated potential predictability is often high in regions of high interannual variance (e.g. local maxima in northern Australia in Figs 1 and 3), the magnitude of the interannual variance does not, in general, indicate whether seasonal-mean temperature is potentially predictable. For example, there is low interannual variance of seasonal-mean surface minimum temperature along the north coast of Australia from OND to DJF (Fig. 2), but generally high estimated potential predictability (Fig. 4). Thus the low interannual variance is dominated by the variance of the slow component. In contrast, there is low interannual variance and potential predictability for surface minimum temperature over southeastern Australia for SON, indicating that the interannual variance there is dominated by the variance of the intraseasonal component.

Jones and Trewin (2000a) found differences between the two temperature variables in their relationship with the SOI, which represents slowly varying boundary forcing by SST. The annual cycle of potential predictability is similar to that of the SOI-temperature correlation, including the differences between surface maximum and minimum temperature. In addition to SST-related variability, GFZ09 argued that major teleconnections such as the Southern Annular Mode (SAM) and soil-moisture content may also be sources of potential predictability. Recent reviews (e.g. Murphy and Timbal 2008, Risbey et al. 2009) have examined the influences on Australian rainfall variability. Given the strong relationship between Australian rainfall and temperature (e.g. Jones 1999), it is likely that similar influences may operate on Australian surface temperature. Indeed, an early study by Frederiksen and Zheng (2005) found modes of coupled variability in the slow component in DJF between Australian surface mean temperature and ENSO and SAM-related variability in the 500 hPa geopotential height. Another source of potential predictability is the recent observed trend in Australian surface temperature (CSIRO 2007). When the AWAP data were detrended, very similar behaviour in estimated potential predictability was found (not shown), but with small decreases. The decreases are generally less than 20 per cent of the values shown in Figs 3 and 4, except for a band around 140°E for surface maximum temperature in JAS and ASO, and in parts of northeastern Australian from ASO to NDJ for surface minimum temperature.

For regions and seasons with high potential predictability, the interannual variance of the seasonal mean is dominated by the variance of the slow component. In this case, long-range forecasts are more likely to have predictive skill, since the underlying processes are more likely to be predictable a season or more ahead. However, for regions and seasons where there is low estimated potential predictability the contribution to the interannual variance is mainly from the intraseasonal component and long-range forecasts are less likely to be skillful.

Finally, the potential predictability of Australian rainfall is also of interest. However, the constraints used here (Eqns 5–7) to estimate the variance of the intraseasonal component are unlikely to be appropriate for rainfall. Instead, a recent
Fig. 3. Estimated potential predictability (%) of AWAP surface maximum temperature from 1958–2007 for all 12 three-month seasons.
Fig. 4. As in Fig. 3, but for AWAP surface minimum temperature from 1958–2007.
study of the intraseasonal covariance between Australian rainfall and atmospheric circulation (Frederiksen et al. 2011), using an appropriate statistical model of daily rainfall, suggested an alternative estimate for the variance of the intraseasonal component. In future work, we intend to apply this to estimate the potential predictability of Australian rainfall.

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References


Appendix

For a three-month season, monthly moments can be defined as follows:

\[
\frac{1}{Y} \sum_{j=1}^{Y} (x_{1j} - x_{2j})^2 \equiv a, \quad \ldots (11)
\]

\[
\frac{1}{Y} \sum_{j=1}^{Y} (x_{1j} - x_{2j}) (x_{2j} - x_{3j}) \equiv b, \quad \ldots (12)
\]

\[
\frac{1}{Y} \sum_{j=1}^{Y} (x_{2j} - x_{3j})^2 \equiv c. \quad \ldots (13)
\]

Equation 1 implies that monthly differences arise entirely from the interseasonal component, e.g. \(x_{1j} - x_{2j} = \varepsilon_{1j} - \varepsilon_{2j}\). Therefore the variance of the difference in the intraseasonal component can be expressed as

\[
E(\varepsilon_{1j} - \varepsilon_{2j})^2 = E(x_{1j} - x_{2j})^2 = \frac{1}{Y} \sum_{j=1}^{Y} (x_{1j} - x_{2j})^2 = \sigma_1^2 - 2\sigma_2\sigma_{12}\phi_{12} + \sigma_2^2 \ldots (14)
\]

From Eqns 11–13 it is therefore possible to express the variances and inter-monthly correlations of the intraseasonal component within a season using monthly moments, i.e.

\[
\sigma_1^2 - 2\sigma_2\sigma_{12}\phi_{12} + \sigma_2^2 = a, \quad \ldots (15)
\]

\[
\sigma_2\sigma_{12} - \sigma_1\sigma_{13} - \sigma_2^2 + \sigma_2\sigma_{23} = b, \quad \ldots (16)
\]

\[
\sigma_2^2 - 2\sigma_2\sigma_{23} + \sigma_3^2 = c. \quad \ldots (17)
\]

Equations 15–17 represent three equations with six unknowns. However, when the constraints proposed by GFZ09 (Eqns 5–7) are applied, the system of equations is reduced to

\[
(\sigma_2 - \beta)^2 - 2\sigma_2(\sigma_2 - \beta)\phi_{12} + \sigma_2^2 = a, \quad \ldots (18)
\]

\[
\sigma_2^2 (2\phi_{12} - 1) = b, \quad \ldots (19)
\]

\[
(\sigma_2 + \beta)^2 - 2\sigma_2(\sigma_2 + \beta)\phi_{12} + \sigma_2^2 = c, \quad \ldots (20)
\]

i.e. three equations with three unknowns. Equations 18–20 can be rearranged to obtain a cubic equation for \(\phi_{12}\):

\[
A\phi_{12}^3 + B\phi_{12}^2 + C\phi_{12} + D = 0, \quad \ldots (21)
\]

where

\[
A = a + 2b + c, \quad \ldots (22)
\]

\[
B = -\frac{5}{2}A - b - \frac{(c - a)^2}{4b}, \quad \ldots (23)
\]

\[
C = 2A + 2b + \frac{(c - a)^2}{4b}, \quad \ldots (24)
\]

\[
D = -\frac{1}{2}A - b - \frac{(c - a)^3}{16b}. \quad \ldots (25)
\]

\(\phi_{12}\) is taken to be the real root of Eqn 21, constrained to lie in [0, 0.1] in order to reduce estimation error (Zheng et al. 2000). \(\sigma_2\) and \(\beta\) are then found by back-substitution of into Eqns 18 and 20. \(\hat{V}(\varepsilon_{1j})\) is estimated at each location by substitution of these three terms into the right hand side of Eqn 8.