PROJECT 1.3: QUANTIFICATION OF THE LIMITS OF SEASONAL PREDICTABILITY OF WA RAINFALL AND SURFACE TEMPERATURE

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Objectives

- To develop new techniques for identifying the upper limits to the predictability of surface temperature and rainfall in all seasons.
- To quantify the predictive characteristics of seasonal climate and report on the efficacy of developing better statistical or dynamical seasonal forecast schemes.

Key Research Findings

- Two new techniques have been developed for estimating the predictive characteristics of WA surface temperature and rainfall in all three month seasons. The methods have been developed as major extensions of previous techniques developed by the principal investigator and other authors.
- The underlying principle of the methodologies is the separation of the total interannual variance of the seasonal mean of the climate variable into two components. One of these components is related to variability within the season and is generally considered to be unpredictable at the "long-range", that is, a season or more before the forecast period. The other component is associated with slowly varying external forcings on the atmosphere (e.g. sea surface temperature (SST), greenhouse gas forcing) and slowly varying (interannual or longer time scale) internal atmospheric variability.
- The methods have been applied to observed WA surface temperature and rainfall to estimate their potential predictability. The results suggest that WA

maximum and minimum surface temperature have fairly high potential predictability in all seasons over wide spread areas of the state. The spatial patterns of potential predictability are generally quite different for maximum and minimum temperature, suggesting there are different processes involved. There are also quite large spatial variations in the patterns between different seasons.

- The results suggest that slow processes related to external forcing such as, for example, sea surface temperature variability, and slow internal dynamics dominate the interannual variance of surface temperature. Consequently, surface temperature is highly potentially predictable and it would be worthwhile to further investigate the slow processes, or drivers, responsible for this. It is also expected that dynamical and statistical (once the slow processes and drivers have been identified) forecast schemes would have fairly high predictive skill.
- Rainfall variability has been found to be dominated by intraseasonal processes, which at the long range are essentially unpredictable. Consequently, the potential predictability of WA rainfall is lower than for surface temperature. However, there are seasons when the potential predictability is relatively high over some regions of the state. Over the SWWA, the potential predictability ranges between 20-30% during the winter seasons MJJ and JJA; there is much less potential for seasonal prediction in the other seasons. The highest potential predictability over northwest WA occurs during the summer seasons DJF and JFM.

MILESTONE 1.3.1: FORMULATION OF, AND REPORT ON, NEW TECHNIQUES FOR IDENTIFYING PREDICTIVE CHARACTERISTICS OF SURFACE TEMPERATURE AND RAINFALL IN ALL SEASONS

Background

Summary

Two new techniques have been developed for estimating the predictive characteristics of WA surface temperature and rainfall in all three month seasons. The methods have been developed as major extensions of previous techniques developed by the principal investigator and other authors. The underlying principle of the methodologies is the separation of the total interannual variance of the seasonal mean of the climate variable into two components. One of these components is related to variability within the season and is generally considered to be unpredictable at the "long-range", that is, a season or more before the forecast period. The other component is associated with slowly varying external forcings on the atmosphere (e.g. sea surface temperature (SST), greenhouse gas forcing) and slowly varying (interannual or longer time scale) internal atmospheric variability. This component is often referred to as the "slow" component and may be regarded as "potentially" predictable because the slowly varying external forcings or internal dynamics may themselves be predictable. The ratio of the slow component to the total interannual variance gives a measure of the potential predictability of the climate variable.

Previous methods have assumed that the climate variable under consideration represented a stationary process with the same monthly statistics, such as, for example, the monthly variance and intermonth correlation. While this is true for many climate variables in some seasons, it is not true for all seasons and all climate variables. Here, we have developed new methodologies with less restrictive assumptions. For WA surface temperature we assume that standard deviation varies linearly across a season, but that the intermonth correlations in temperature are stationary. Rainfall, which consists of dichotomous (on/off) events, is more problematical. For this field, we have developed a completely general methodology. It

requires daily data to estimate the intermonth correlations within a season, and monthly data to estimate the components of variance. Both methodologies have been applied to WA surface climate and have been published in three peer-reviewed journal publications

Introduction

Outside the tropics, it is known that a substantial component of the total interannual variability of seasonal mean climate fields arises from variability within the season (e.g. Madden 1976; Trenberth 1985; Zheng et al. 2004). In the tropics, where a clear "signal" in seasonal mean variability has been observed (e.g. Trenberth 1985; Zheng et al. 2000), variability within the season is also quantifiable. Atmospheric processes with time scale longer than the deterministic prediction period, of about ten days, but less than a season (e.g. extratropical blocking, the Madden-Julian Oscillation (MJO)) are responsible for this variability. This is because atmospheric processes within the deterministic period (e.g. mid-latitude storms) are effectively filtered out when applying the seasonal mean average. This component of the interannual variability has been variously referred to as "natural variability" (Madden 1976), "climate noise" (e.g. Madden 1981; Nicholls 1983), "weather noise" or the "intraseasonal" component of interannual variability (Zheng and Frederiksen 2004). The intraseasonal component of interannual variability is more likely to be related to the "noise", and is essentially unpredictable at the long range (a season or more ahead).

The removal of the intraseasonal component of variability from the total variability of the seasonal mean results in a residual component that is more likely to be associated with slowly varying external forcings on the atmosphere (e.g. sea surface temperature (SST)) and with slowly varying (interannual and longer time scale) internal atmospheric variability (e.g. the Quasi-Biennial Oscillation). In this context, the residual component is more likely to be related to the "signal". The residual has often been called the "potential predictable" component, since it is likely to be associated with forcings that are potentially predictable at the long range (Madden 1976) such as sea surface temperature or changes in greenhouse gas concentrations. The residual has also been called the "slow" component of interannual variability (e.g. Zheng and

Frederiksen 2004). “Potential predictability” is generally defined as the ratio of the slow component to the total interannual variability.

Estimates of the potential predictability, or limits to predictability, have generally been based on the removal of the estimated intraseasonal component of variability. This was first done by Madden (1976) for Northern Hemisphere sea level pressure using frequency domain estimation and daily data. Nicholls (1981, 1983) used this method to estimate the potential predictability for Australian surface pressure and surface mean temperature using a limited dataset of Australian observing stations.

More recently, Zheng et al. (2000, 2004) and Zheng and Frederiksen (2004) proposed a methodology based on using monthly mean data and moment estimations to estimate the variance due to the intraseasonal component. Central to this and earlier methods is the assumption of stationarity in the monthly or daily time series. Zheng and Frederiksen (2004) noted, for example, while these assumptions are probably reasonable in summer and winter (December-January-February (DJF) and June-July-August (JJA) respectively for the Southern Hemisphere), they may not apply well in transition seasons (e.g. March-April-May (MAM) or September-October-November (SON)). These assumptions are also unlikely to hold true for climate variables, such as rainfall, which consist of dichotomous (on/off) events.

Technical Details

Estimating the Potential Predictability of WA surface climate

Here, we present a brief overview of the methodologies that has been developed to cater for estimating the potential predictability of climate variables in transition seasons and for variables like rainfall. A detailed description of the methods appears in the three papers Frederiksen et al. (2008) and Grainger et al. (2008, 2009) (see publications at the end of this report). Frederiksen and Zheng (2007) provide an overview of the general framework for these methods.

The statistical model used to conceptually decompose the monthly mean of a climate variable, x, after removing the annual cycle, is

$$x_{ym} = \mu_y + \varepsilon_{ym} , \qquad (1)$$

where m (m = 1, 2, 3) is the month index in the season, y (y = 1, …, Y) is the year index and Y is the total number of years, μ_y is the population seasonal mean and ε_{ym} is the residual monthly departure of x_{ym} from μ_y

The average taken over an independent variable (i.e., m or y) can be represented with the subscript "o". In that case, a seasonal mean can be written as

$$x_{yo} = \mu_y + \varepsilon_{yo} , \qquad (2)$$

where x_{yo} is associated with the seasonal mean (also referred to in this study as the "total" field), ε_{yo} with the intraseasonal component and μ_y with the slow component of variability.

In practice, μ_y and ε_{ym} (Eq. (1)), or μ_y and ε_{yo} (Eq. (2)), cannot be directly calculated. However, it is possible to estimate the interannual variance $V(\varepsilon_{yo})$ of the intraseasonal component using monthly data. This is because Eq. (1) implies that monthly differences arise entirely from the intraseasonal component $\{\varepsilon_{y1}, \varepsilon_{y2}, \varepsilon_{y3}\}$, e.g.

$$x_{y1} - x_{y2} = \varepsilon_{y1} - \varepsilon_{y2} . \qquad (3)$$

In general, the interannual variance of ε_{ym} can be written as

$$V(\varepsilon_{ym}) = \sigma_m^2, m = 1, 2, 3 . \qquad (4)$$

The inter-monthly correlations, $C(\varepsilon_{ym}, \varepsilon_{yn})$, can then be defined as

$$C(\varepsilon_{ym}, \varepsilon_{yn}) = \frac{V(\varepsilon_{ym}, \varepsilon_{yn})}{\sigma_m \sigma_n} = \phi_{mn}, m, n = 1, 2, 3, m \neq n , \qquad (5)$$

where $V(\varepsilon_{ym}, \varepsilon_{yn})$ denotes the covariance between the intraseasonal components in months m and n. The interannual variance of the intraseasonal component can then be expressed as

$$V(\varepsilon_{yo}) = E\left(\frac{1}{3}\sum_{m=1}^{3}\varepsilon_{ym}\right)^2$$

$$= \frac{1}{9}\left[V(\varepsilon_{y1}) + V(\varepsilon_{y2}) + V(\varepsilon_{y3}) + 2V(\varepsilon_{y1},\varepsilon_{y2}) + 2V(\varepsilon_{y2},\varepsilon_{y3}) + 2V(\varepsilon_{y1},\varepsilon_{y3})\right]$$

$$= \frac{1}{9}\left[\sigma_1^2 + \sigma_2^2 + \sigma_3^2 + 2(\sigma_1\sigma_2\phi_{12} + \sigma_2\sigma_3\phi_{23} + \sigma_1\sigma_3\phi_{13})\right], \tag{6}$$

where E denotes the expectation value over all years. The right hand side of Eq. (6) comprises six parameters which need to be estimated from the observations $\{x_{ym}, y = 1, \ldots, Y, m = 1, 2, 3\}$. Three equations linking these parameters can be derived based on our conceptual model Eq. (1) in the following manner:

Firstly, the variance of $x_{y1} - x_{y2}$ can be expressed as

$$E\left[(x_{y1} - x_{y2})^2\right] \approx \frac{1}{Y}\sum_{y=1}^{Y}(x_{y1} - x_{y2})^2 \equiv a\,, \tag{7}$$

and using Eqs. (3)-(5), it can also be expressed as

$$E\left[(x_{y1} - x_{y2})^2\right] = E\left[(\varepsilon_{y1} - \varepsilon_{y2})^2\right] = \sigma_1^2 - 2\sigma_1\sigma_2\phi_{12} + \sigma_2^2\,. \tag{8}$$

Therefore, we can derive the following equation

$$\sigma_1^2 - 2\sigma_1\sigma_2\phi_{12} + \sigma_2^2 \approx a\,. \tag{9}$$

In a similar manner, two more equations can be derived:

$$\sigma_1\sigma_2\phi_{12} - \sigma_1\sigma_3\phi_{13} - \sigma_2^2 + \sigma_2\sigma_3\phi_{23} \approx b\,, \tag{10}$$

$$\sigma_2^2 - 2\sigma_2\sigma_3\phi_{23} + \sigma_3^2 \approx c\,, \tag{11}$$

where

$$b \equiv \frac{1}{Y}\sum_{y=1}^{Y}(x_{y1} - x_{y2})(x_{y2} - x_{y3})\,, \tag{12}$$

$$c \equiv \frac{1}{Y}\sum_{y=1}^{Y}(x_{y2} - x_{y3})^2\,. \tag{13}$$

The variables a, b and c in Eqs. (9)-(11) represent monthly moments of x and can be directly sampled.

Three more equations are necessary. In previous studies (see Frederiksen and Zheng, 2007 for overview), three important restrictions were assumed throughout a season. Firstly, the variance and inter-monthly correlation (Eqs. (4) and (5)) were assumed to be stationary. That is,

$$\sigma_1 = \sigma_2 = \sigma_3 = \sigma\,, \tag{14}$$

$$\phi_{12} = \phi_{23}. \tag{15}$$

Also, recognizing that day-to-day weather events are unpredictable beyond a week or two, a reasonable assumption is that the intraseasonal components are uncorrelated if they are a month or more apart, i.e.

$$\phi_{13} = 0. \tag{16}$$

These assumptions are not necessarily true for the transition seasons (autumn and spring) and even less likely to be true for climate variables like rainfall.

Our analysis of WA surface temperature (Grainger et al., 2008, 2009) shows that, to first order, a linear model between the monthly standard deviations within each season is a reasonable assumption during transition seasons. That is, we assume that the standard deviation of ε_{ym} varies linearly across a season by a parameter, β:

$$\sigma_1 = \sigma_2 - \beta, \tag{19}$$

$$\sigma_3 = \sigma_2 + \beta. \tag{20}$$

To ensure that all standard deviations are positive, it is necessary that

$$|\beta| < \sigma_2. \tag{21}$$

For surface temperature, it turns out that assumptions Eqs (15) and (16) on the intermonth correlation are also reasonable. This allows the interannual variance of the intraseasonal component to be estimated in all seasons.

Rainfall consists of daily dichotomous events and the above assumptions can not be used. However, an estimate of the interannual variance Eq. (6) can be made using a two state, first order, Markov chain model (Wilks, 2006) fitted to daily rainfall data to estimate the intermonth correlation between monthly means of the rainfall during a season. Thus, Eqs (9)-(11) can be used to solve for σ_m. The exact procedure and equations used to solve this problem can be found in Frederiksen et al. (2008) (see publications at the end of this report).

Once an estimate of $V\left(\varepsilon_{yo}\right)$ has been made, the potential predictability of the seasonal mean climate variables can then be estimated as follows. The total interannual variability of the seasonal mean can be estimated from the sample variance, i.e.

$$V\left(x_{yo}\right) = \frac{1}{Y-1}\sum_{y=1}^{Y}\left(x_{yo} - x_{oo}\right)^{2} . \qquad (22)$$

The potential predictability is then defined as the fraction of the interannual variability of the seasonal mean that is not due to the intraseasonal variance, i.e.

$$Potential\,Predictability \equiv 1 - \frac{V\left(x_{yo}\right)}{V\left(x_{yo}\right)}. \qquad (23)$$

In other words, it is the fraction of the interannual variance due to "slow" processes associated with external forcings (sea surface temperature, changes in greenhouse gases) and very slowly evolving internal dynamics.

Conclusions

New methodologies for estimating the potential predictability of WA surface temperature and rainfall have been derived. These can be used to estimate the fraction of the interannual variance in the WA climate variable that is related to slow processes (sea surface temperature, etc.) and is therefore potentially predictable. This can be used as a measure of the upper limit to the predictive skill of seasonal forecast schemes from either dynamical or statistical models. The application of these new methods is discussed below in our report on milestone 1.3.2, and also in Frederiksen et al. (2008) and Grainger et al. (2008, 2009) (see publications at the end of this report).

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MILESTONE 1.3.2: REPORT ON PREDICTBILITY OF WA's SURFACE CLIMATE WITH GUIDANCE ON WHERE BEST INVESTMENTS CAN BE MADE IN SEASONAL FORECASTING

Background

Summary

New methods have been applied to observed WA surface temperature and rainfall to estimate their potential predictability. The results suggest that WA maximum and minimum surface temperature have fairly high potential predictability in all seasons over wide spread areas of the state. The spatial patterns of potential predictability are generally quite different for maximum and minimum temperature, suggesting there are different processes involved. There are also quite large spatial variations in the patterns between different seasons.

Our results suggest that slow processes related to external forcing such as, for example, sea surface temperature variability, and slow internal dynamics dominate the interannual variance of surface temperature. Consequently, surface temperature is highly potentially predictable and it would be worthwhile to further investigate the slow processes, or drivers, responsible for this. It is also expected that dynamical and statistical (once the slow processes and drivers have been identified) forecast schemes would have fairly high predictive skill.

Rainfall variability has been found to be dominated by intraseasonal processes, which at the long range are essentially unpredictable. Consequently, the potential predictability of WA rainfall is lower than for surface temperature. However, there are seasons when the potential predictability is relatively high over some regions of the state. Over the SWWA, the potential predictability ranges between 20-30% during the winter seasons MJJ and JJA; there is much less potential for seasonal prediction in the other seasons. The highest potential predictability over northwest WA occurs during the summer seasons DJF and JFM.

Introduction

Climate variability has a major impact on the Western Australian (WA) economy, primarily through its direct impact on agriculture. Climate variability can be managed to some extent through the provision of seasonal forecasts (e.g. Fawcett et al. 2005), the skill of which can be assessed. This raises the issue of where efforts and funds should be directed for better understanding the large-scale processes upon which the provision of skilful forecasts relies. In particular, what are the regions and seasons where WA surface climate is potentially predictable?

No systematic estimate of the upper limit of predictability of WA surface climate, and implicitly the upper limit to the predictive skill of statistical or dynamical seasonal forecasts schemes, has been attempted before. Current statistical forecast schemes (Fawcett et al., 2005) rely on sea surface temperatures in the Pacific and Indian oceans as predictors (Drosdowsky, 1993; Nicholls, 1989; Jones, 1998; Jones and Trewin, 2000a). Dynamical models, while they incorporate a comprehensive number of physical processes, also largely rely on their forecast skill in capturing the interannual variations in sea surface temperatures in these ocean basins.

The methodologies described in milestone report 1.3.1 above, provide an estimate of the relative importance of slow processes in the interannual variability of season means in WA surface temperature and rainfall. These slow processes include sea surface temperature forcing but also other processes such as changes in greenhouse gases, and slowly varying internal dynamics (e.g. the slow Southern Annular Mode). The fraction of the interannual variance attributable to these slow processes is a measure of the potential predictability of the climate variable, and because it implicitly incorporates all slow processes it may be considered an upper limit.

In the following sections we briefly discuss the results, and implications, of the application of our methodologies to WA surface temperature and rainfall. A more detailed analysis can be found in Frederiksen et al. (2008) and Grainger et al. (2008, 2009) (see publications at the end of this report).

Technical Details

The Potential Predictability of WA Surface Temperature

We have applied our methodology to monthly means of surface maximum and minimum temperature obtained from the Australian Bureau of Meteorology National Climate Centre (NCC) gridded historical dataset (e.g. Jones and Trewin 2000b) for the period 1950-2000. This uses 95 observing stations from the High Quality network described by Trewin (2001). Although the network of the stations is spatially inhomogeneous (see Jones and Trewin 2000b, Fig.1) they concluded that it is "capable of providing very significant information about the structure of temperature anomalies across most, if not all, of Australia". The data were interpolated from the supplied $0.25^{o} \times 0.25^{o}$ grid to a $1^{o} \times 1^{o}$ grid at land points only. The choice of resolution is arbitrary, but has been used in earlier studies (e.g. Jones and Trewin 2000a, b), and is the resolution of the seasonal forecasts issued by NCC (Fawcett et al. 2005).

Figures 1.3.1 and 1.3.2 show the estimated potential predictability for Western Australian surface maximum temperature and minimum temperature, respectively, for all twelve three month seasons expressed as a percentage of the total interannual variance of these fields. There is a distinct annual cycle in the predictability of both temperatures, but generally there are large areas of the state where the potential predictability is very high in all seasons. It is also noticeable, that the spatial structure of the pattern of predictability for maximum temperature is quite different from the corresponding pattern for minimum temperature in all seasons.

The causes of the differences in surface maximum and minimum temperature variability have been considered by a number of authors. For example, Jones (1999) found different relationships between area-averaged rainfall and surface maximum and minimum temperature. The different patterns of variability have also been attributed to differences in the physical processes involved in determining daily surface maximum and minimum temperature, which can be considered in terms of the diurnal cycle of the surface energy budget (Watterson 1997; Power et al. 1998).

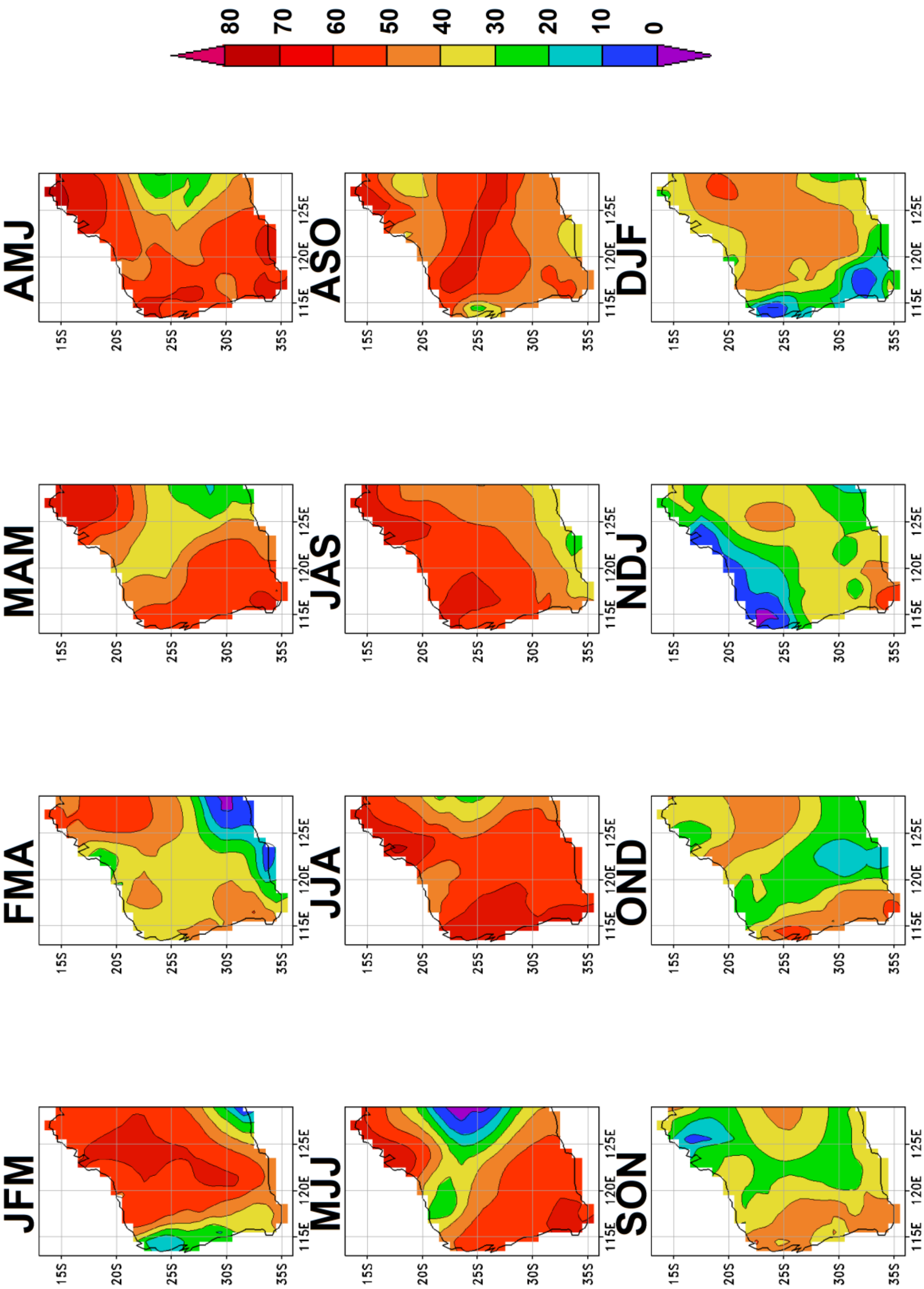

Figure 1.3.1 Potential Predictability (%) of WA Maximum Temperature as a fraction of total interannual variance.

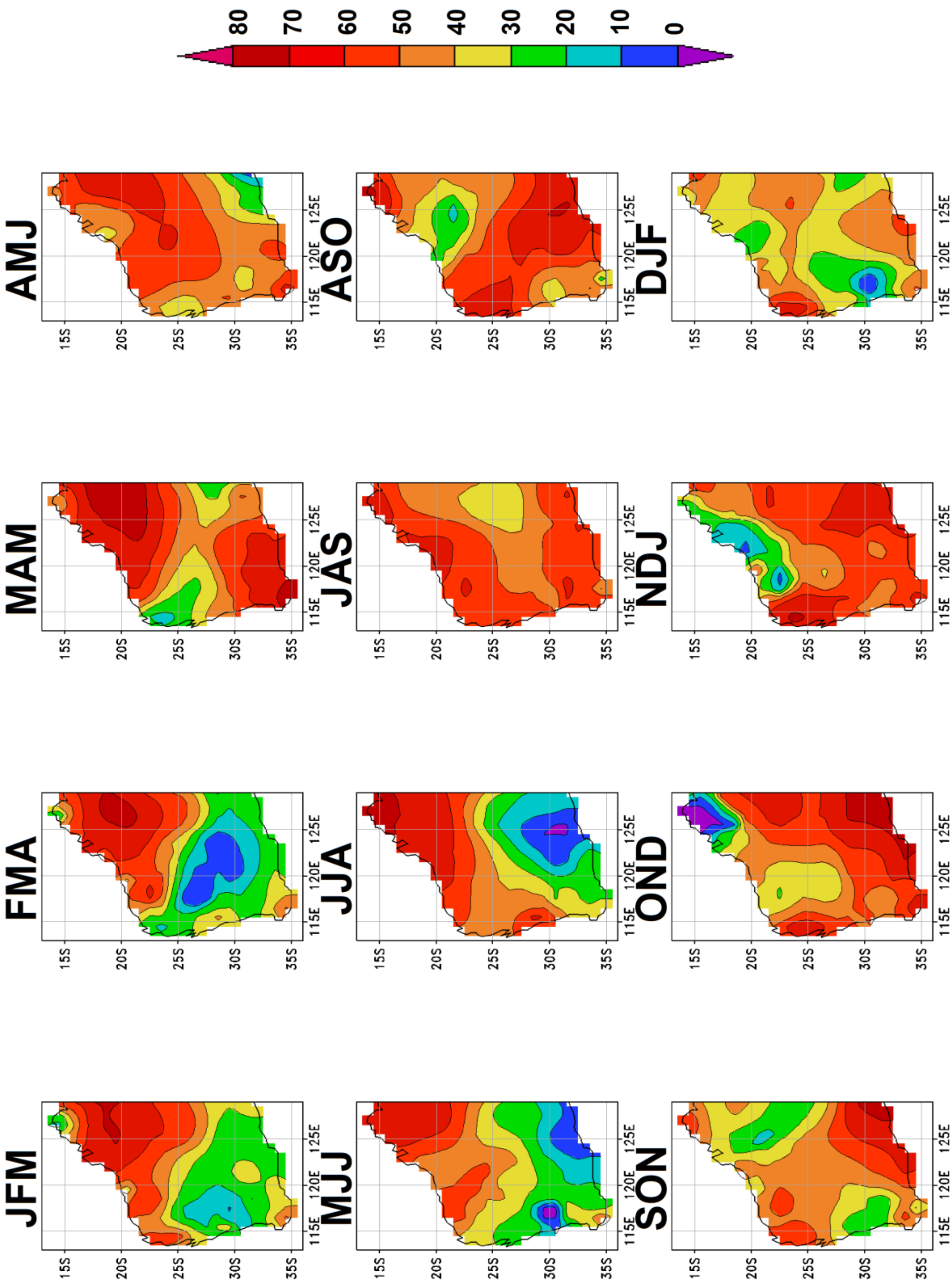

Figure 1.3.2 Potential Predictability (%) of WA Minimum Temperature as a fraction of total interannual variance.

The estimated potential predictability of surface maximum temperature (Fig. 1.3.1) is generally high (at least 50%) north of 20S throughout most of the year, except during SON, OND and NDJ. State-wide, the predictability is lowest during the seasons SON-DJF. The lowest predictability occurs along the west coast during DJF and JFM; along the northwest coast during NDJ; the south of the state during FMA; over the central east of the state during MJJ. In southwest WA (SWWA), the predictability is generally greater than 30% and can exceed 60% in all seasons except during DJF.

Like the maximum temperature, the potential predictability of the minimum temperature is generally high north of 20S (with some regions exceeding 70%), although it is much lower in OND. The lowest potential predictability tends to occur over a large area south of 25S during JFM, FMA, MJJ and JJA. In most other seasons there is generally good predictability (greater than 40%) over much of the state. As for maximum temperature, predictability in SWWA is generally greater than 30% in all seasons and can exceed 60%. To put this in perspective, the largest correlations with ENSO occur over eastern Australia with values about 0.6. This is equivalent to explaining about 36% of the variance, and this is regarded as being highly predictable.

Overall, both maximum and minimum temperatures are potentially highly predictable over large parts of the state in all seasons.

The Potential Predictability of WA Rainfall

As explained above, rainfall is a much more difficult climate field when it comes to estimating the potential predictability. So, in order to minimise the estimation errors we have applied our methodology using only daily and monthly NCC rainfall data near the 360 high quality stations shown in Fig. 1.3.3, and have used a 3 pass Barnes (1964) interpolation to extend our estimate to all Australia. We have used data for the period 1958-2006.

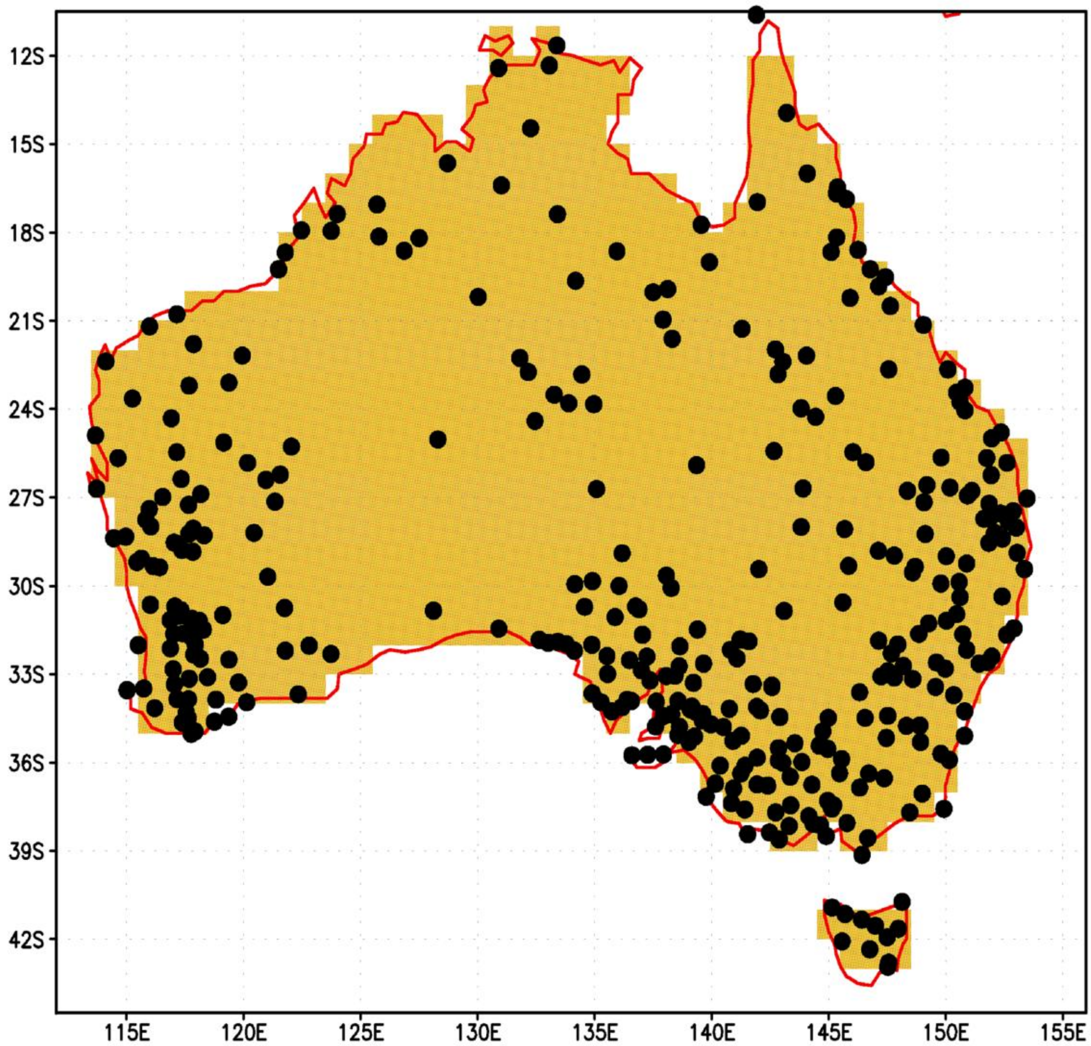

Figure 1.3.3 High quality monthly rainfall stations

Figure 1.3.4 shows the estimated potential predictability of WA rainfall for each twelve three month season. When compared with the corresponding plots for WA surface temperature (Figs. 1.3.1 and 1.3.2), it is clear that intraseasonal processes play a much larger role in the interannual variation of the seasonal mean rainfall. Consequently, rainfall is much less predictable at the long range.

As for temperature, there is a distinct annual cycle in the pattern of potential predictability. From NDJ to AMJ, the potential predictability is very low north of 20S, indicating that intraseasonal processes dominate. This is also the period when much of the weather over the north is governed by the Madden-Julian-Oscillation (MJO) which would account for the low predictability. South of 20S, during these seasons, predictability varies between 20-40% over large areas of the state, especially during DJF and JFM. Largest predictability (as high as 70%) occurs over northern WA during MJJ, JJA, SON and OND. During spring (SON and OND) there is also substantial predictability over central WA including near the coast. Over SWWA, predictability during MJJ and JJA ranges between 20-30%, indicating that there is some potential for long range skilful seasonal prediction during these seasons. During the rest of the year there is very low predictability over the SWWA.

Conclusions

In this study, new methodologies have been applied to estimate the potential predictability of WA surface temperature and rainfall. The aim has been to elucidate those regions and seasons where there is some potential for performing skilful long range seasonal predictions of these fields. Past experience suggests that a potential predictability of 20-30% is likely to provide some benefit and reasonably skilful prediction.

In general, surface maximum and minimum temperatures have quite high potential predictability in all seasons over wide areas of the state. In particular, this is the case for SWWA with predictability generally greater than 30% in all seasons, except DJF for maximum temperature. Over northwest WA the surface temperature predictability is also quite high except during NDJ when the predictability maximum temperature is less than 10%. Overall, surface maximum and minimum temperature show high potential for long range prediction.

Compared with surface temperature, WA rainfall is much less potentially predictable and intraseasonal processes dominate the interannual variance over wide spread regions of the state. However, there are seasons and regions where the potential predictability is relatively high. Over the SWWA, the potential predictability ranges between 20-30% during the winter seasons MJJ and JJA; there is much less potential for seasonal prediction in the other seasons. The highest potential predictability over northwest WA occurs during the summer seasons DJF and JFM.

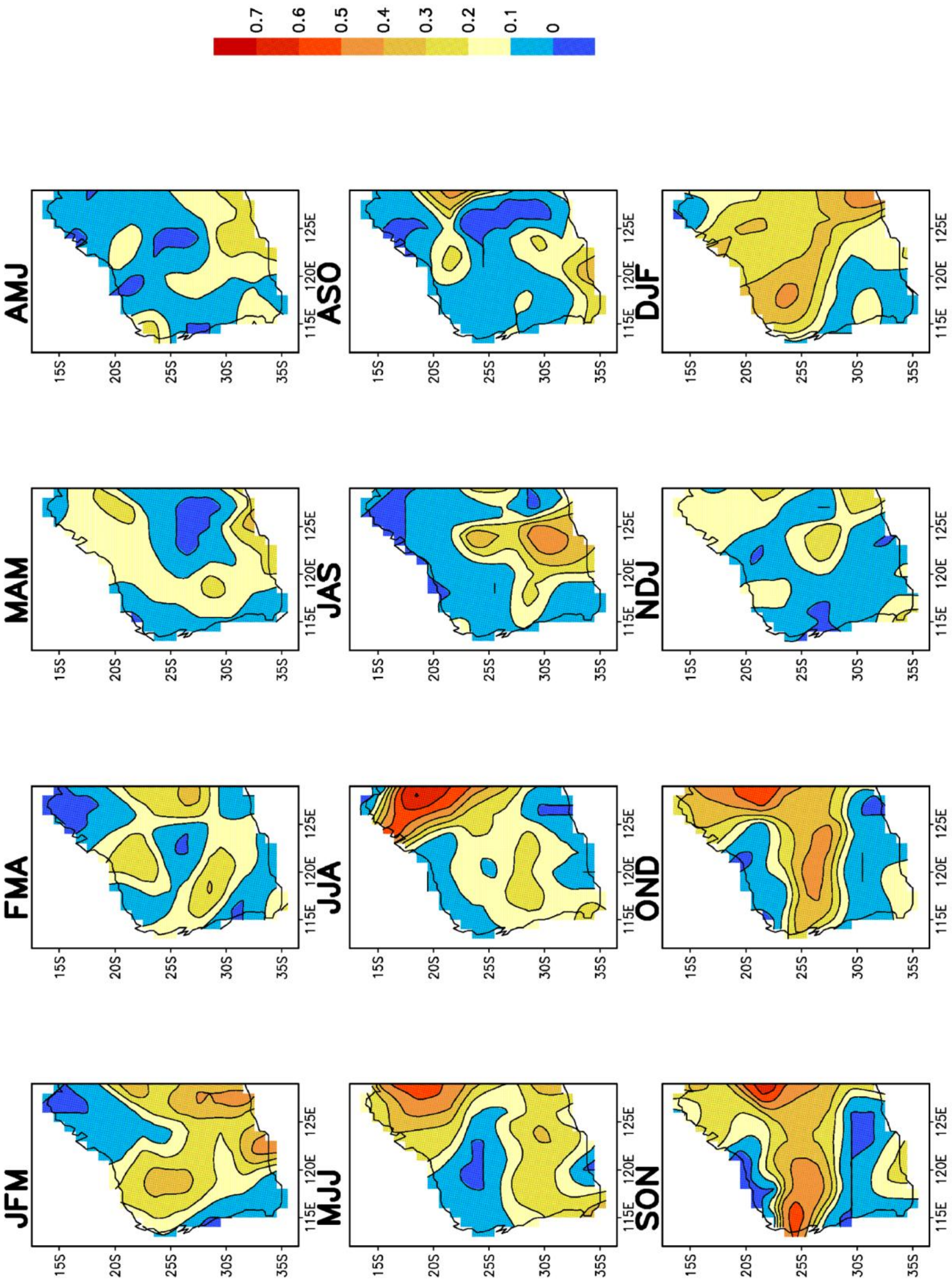

Figure 1.3.4 Potential Predictability of WA Rainfall as a fraction of total interannual variance.

While the methods used in this study are able to provide spatial patterns of potential predictability, it is not possible to identify the precise nature of the slow processes that gives rise to this predictability. There are, however, other techniques formulated by the principal investigator which could be used to begin to identify these factors. These methods rely on identifying large scale drivers of climate variability that couple to the surface fields. However, this is beyond the scope of this current project and would require additional funding to be pursued.

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