Climate variability and predictability for southwest Western Australia

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Report of Second Research Phase

for the

Indian Ocean Climate Initiative

"You get a quite different set of meteorological conditions in the Indian Ocean – quite different. Any fool knows that." (quoted in *Down Under*, Bill Bryson, Doubleday, 2000).

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SUMMARY OF BMRC PHASE 1 IOCI WORK (FROM NICHOLLS ET AL., 1999)

“BMRC has, through the first half of the IOCI (1998-99), been investigating the following problems, for the southwest of Western Australia:

- Selection of high-quality climate data for the southwest
- How surprising is the decrease in rainfall?
- Has extreme rainfall declined as well as total rainfall?
- Is the rainfall decrease due to changes in atmospheric circulation?
- Is the rainfall decrease attributable to changes in Indian Ocean SSTs?
- Can we develop better methods for seasonal prediction in the southwest?
- How does the El Niño - Southern Oscillation affect southwest rainfall?
- Can climate models help us in seasonal prediction in the southwest?

Our achievements and preliminary conclusions from this work include:

- We have selected stations with high-quality daily/monthly rainfall, and daily temperature data over a long period, for analysis. These data sets can be made available to others interested in using high-quality climate data for the southwest.

- We have fitted statistical models to station rainfall and estimated the likely frequency of the observed runs of dry years in recent decades. They are unusual, in the historical context. We also have estimated breakpoints in the rainfall data series, where there is a sudden change in mean rainfall. The date of these breakpoints shows considerable spatial consistency, indicating that the breaks are real physical phenomena.

- Changes in the numbers of days of rain, and the amount of rain falling in extreme events, both have contributed to the decline in total rainfall.

- About half of the observed decline in rainfall is related to changes in regional atmospheric circulation, as represented by Perth atmospheric pressure. Part of the observed increase in Perth pressure represents changes in the El Niño - Southern Oscillation, as measured by the SOI. However, little of the observed rainfall decline is attributable to long-term changes in the El Niño - Southern Oscillation.

- Interannual variations in Indian Ocean SSTs are only weakly related to southwest rainfall, and even this weak relationship simply represents the effect of the El Niño - Southern Oscillation on both Indian Ocean SST and southwest rainfall, rather than an independent effect of the SSTs on rainfall. Since the interannual variations are not related, it seems unlikely that the long-term changes in both Indian Ocean SSTs and southwest rainfall are causally related. This conclusion is supported by the inability of climate models, when forced with observed SSTs over the 20th century to reproduce the observed decline in southwest rainfall.

- Secular changes have confounded the interannual relationships between the SOI and southwest rainfall, disguising some of the predictability achievable through the use of the SOI. An approach using year-to-year differences in the SOI has been proposed to overcome this confounding effect.”

BMRC PROPOSAL FOR IOCI SECOND RESEARCH PHASE (JULY 1999-DECEMBER 2000) AGREED JUNE 1999

1. Specific seasonal climate forecast system for SWWA

- Develop techniques using changes in the SOI from year-to-year, to predict southwest WA rainfall for selected stations at selected times of the year and at selected lead-times.
- The possibility of developing an operational system for predicting summer climate factors, especially those relating to water demand, also will be investigated using near-global SSTs and the SOI.
- The selected stations, seasons, and lead-times of the forecasts have been chosen after discussions with WA agency representatives.
  The stations will include a station representative of the Perth catchments area (Jarrahdale), Manjimup, and Kalgoorlie. If possible, Mingenew, Merredin, and Lake Grace will also be analysed
  The seasons will be winter (for rainfall May-October), and summer (December-February), for factors affecting water demand, eg,, mean temperature, temperature extremes, and rainfall).
- The possibility of developing an operational system for forecasting winter rainfall at the end of April, using the SOI, will be investigated.
- The possibility of forecasting the summer demand factors using September data (SSTs and SOI) will be investigated.
- The possible value of the Antarctic Circumpolar Wave and southern Indian Ocean SSTs in prediction will be examined.

There is a perception that the Southern Oscillation Index (SOI), until recently the basis for operational *seasonal rainfall forecasting in Australia, is less effective in prediction for the southwest, relative to the eastern states. Nicholls (1989) identified a mode of variability of Indian Ocean SST that appeared to be related to rainfall in the south and southeast of the continent, somewhat distinct from the El Nino-Southern Oscillation mode affecting the eastern states. As a result, Drosdowsky and Chambers (1998) developed a new system for seasonal rainfall forecasting, now operationally implemented in the Bureau of Meteorology's National Climate Centre, using Indian and Pacific Ocean SST patterns as predictors (replacing the earlier system which used just the SOI as a single predictor). The new method provides a longer lead time for the predictions, is more stable, and exhibits somewhat increased skill. However, skill in the new system is still greater in the east and north of the country and the system seems less effective in the southwest. At the start of Phase 1, however, it was considered that further development of an SST- based system for seasonal prediction could lead to potentially useful forecasts for the southwest. This was because other work had identified an apparent link between southwest rainfall and Indian Ocean SSTs (eg, Smith et al 1999). However, work in Phase 1 found that interannual variations in Indian Ocean SSTs are only weakly related to southwest rainfall, and even this weak relationship simply represents the effect of the El Nino - Southern Oscillation on both Indian Ocean SST and southwest rainfall, rather than an independent effect of the SSTs on rainfall. Phase 1 work also revealed that secular changes have confounded the interannual relationships between the SOI and southwest rainfall, disguising some of the predictability achievable through the use of the SOI. An approach using year-to-year differences in the SOI has been proposed to overcome this confounding effect, and may lead to potentially useful seasonal rainfall forecasts based on the SOI, rather than SSTs. Other Phase I work has indicated that seasonal temperature for the southwest, at least in some seasons, may be predictable using SSTs.*

BMRC Proposal for IOCI Second Research Phase (July 1999- December 2000), agreed June 1999

2. *Causes of decadal decline in rainfall in SWWA*

- Empirical studies and model studies will be used to continue our investigations of the underlying causes of the recent trend in rainfall in the southwest.
- These investigations will include the use of model simulations forced with observed global SSTs, to determine whether the models can simulate the decline in rainfall.
- Path analysis will be used in empirical studies to provide further light on the causes of this decline.
- Variables such as wind direction will be investigated, to determine whether these can explain the apparent decline in rainfall and the secular changes in relationships between, for instance, the SOI and rainfall.

Since the interannual variations of southwest rainfall are not related to interannual variations in Indian *Ocean SSTs (see above), it seems unlikely that the long-term changes in Indian Ocean SSTs and southwest rainfall are causally related. This conclusion is supported by the inability of climate models, when forced with observed SSTs over the 20th century to reproduce the observed decline in southwest rainfall (Phase 1). Further model studies are needed to estimate the predictability of southwest rainfall from SSTs, using long-term simulations of the climate, and experimental model predictions conducted in real-time through 1997-98. As well, empirical studies using a path analysis technique may provide some guidance as to the possible causes of the apparent decline.*

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Additions to BMRC Second Research Phase studies requested by IOCI7, 15 October 1999:

- Examine predictability of September-November rainfall (for agricultural purposes), from data available at end of May, end of June, end of July, using stations selected for winter and summer.
- Examine predictability of September-November temperature (for curing for fire risk), from data available at end of May, end of June, end of July, using stations selected for winter and summer.
- Examine predictability of wheat yield (David Stephens to provide time series of wheat yield data).

Further additions (March-May 2000):

- Investigate whether equatorial Indian Ocean SST dipole is independent of the El Niño - Southern Oscillation, and consider its possible use in seasonal prediction for SWWA.
- Investigate whether long-term variations in SWWA rainfall are related to distant factors (e.g., rainfall trends in other parts of the globe).
- Investigate whether SST gradients in the Indian Ocean are useful predictors for SWWA

RESULTS OF SECOND RESEARCH PHASE

Specific seasonal climate forecast system for SWWA

Seasonal climate predictability

Target forecasts

The forecasts requested were:

- Winter (May to October) rainfall using the SOI and sea surface temperatures (SSTs) up to the end of April
- Spring (September to November) rainfall using the SOI and SSTs up to the end of May, end of June and end of July
- Spring (September to November) temperature (mean, mean maximum and mean minimum) using the SOI and SSTs up to the end of July
- Summer (December to February) rainfall using the SOI and SSTs up to the end of September
- Summer (December to February) mean maximum temperature
- Summer (December to February) temperature extremes

When considering extreme temperatures, the mean maximum temperature, the number of days over 35°C, and the number of days over 40°C were examined.

Method

A statistical forecast scheme similar to that of Drosdowsky and Chambers (1998) and Jones (1998) was adopted. This is an empirical forecast scheme based upon linear discriminant analysis. Lagged values of the predictor variables time series (eg., SST time scores, SOI) are used to forecast the probability of the predictand (eg., rainfall) being in pre-defined categories (terciles - three equally probable categories). Linear Error in Probability Space (LEPS) was used to assess the potential skill of the prediction systems, using cross-validation to account for artificial skill (Drosdowsky and Chambers, 1998). The LEPS skill score ranges from 100 (for perfect forecasts) to –100 (worst possible forecasts). Positive values over indicate potentially useful forecast system. LEPS is notoriously difficult to interpret, other than in relative terms (i.e., comparing two forecast methods). We provide, therefore, scatter diagrams of predictor versus predictand for selected, representative pairs of predictor-predictand, to allow a more ready interpretation of skill. These also illustrate how typical ranges of LEPS translate into more readily interpretable skill scores such as the number of "hits".

Station Information

Available data for the six sites of interest are listed in Table 1. As the forecast models were based on data from 1950 to the present, some filling of the temperature data sets was needed and is described below. For most of the stations in Table 1 additional temperature data, to fill in the missing data, were available from stations within a 100 km (or even 50 km) radius. Table 2 lists the additional temperature stations selected for further testing for each of the stations of interest (Table 1).

Table 1: Station information. * indicates that temperature data is available from 1957 from a site within a few kilometres (09573).

Station Name	Station Number	Rainfall From	Temperature From/To
Mingenew	08088	1896	1965-1975
Jarrahdale	09023	1882	not available
Lake Grace	10592	1912	1956 -
Merredin	10092	1903	1966 -
Manjimup	09619	1900	not available*
Kalgoorlie	12013	1897	not available

Table 2: Additional stations (used for filling missing data).

Station Name	Additional Station Numbers
Mingenew	08025, 08039, 08051, 08093, 08095
Jarrahdale	09021, 09538, 09534, 10648
Lake Grace	10073, 10035, 10536, 10579
Merredin	10007, 10035, 10073, 10093, 10536
Manjimup	09510, 09534, 09538, 09573
Kalgoorlie	10073, 10092, 10093, 12038

A simple linear correlation test was used to select the station (or stations) with the strongest (linear) relationship to the stations in Table 1. In the case where no temperature was recorded at the station in Table 1 the closest station was used and gaps filled using other nearby stations. For Jarrahdale the closest station was 09538, for Manjimup, 09573 and for Kalgoorlie, 12038. Table 3 lists the order in which stations were used to fill gaps. The first station listed was used unless a gap exists in that record, in which case the second station was used, and so on. On all occasions we were able to fill all gaps using the lists in Table 3 and, in most cases, used only the first 2 or 3 stations.

Table 3: Order of stations used to fill gaps in the record.

Station Name	Station Order
Mingenew	08088, 08095, 08093, 08025, 08039
Jarrahdale	09538, 09021, 09534, 10648
Lake Grace	10592, 10536, 10579, 10073, 10035
Merredin	10092, 10093, 10007, 10035, 10073
Manjimup	09573, 09510, 09534, 09538
Kalgoorlie	12038, 10092, 10093, 10073

Linear regression was used to relate the temperature at the stations in Table 1 (or the first station in the list of Table 3) with subsequent stations in the list (Table 3), for gap filling.

Predictors

Time series of the first two principal components (SST1 & SST2) of a near global empirical orthogonal function (EOF) analysis of sea surface temperatures (SST) were included as possible predictors. The first EOF, SST1, (Figure 1) has highest loadings in the central and eastern equatorial Pacific Ocean and in the Indian Ocean and represents the mature phase of an El Niño / Southern Oscillation (ENSO) event. The second EOF, SST2, has highest loadings just west of the Australian continent, extending northwest to the central equatorial region. The southern oscillation index (SOI) was also included as a potential predictor.

Winter (May to October)
Forecasts were made for winter (May to October) rainfall terciles at each of the six stations in Table 1. A number of different predictors were considered:

April SST1;
April SST2;
April SST1 and SST2;
February and April SST1;
February and April SST2;
February and April SST1 and SST2;
February to April (FMA) SST1;
FMA SST2;
FMA SST1 and SST2;
Mean of December to February (DJF) and FMA SST1;
DJF and FMA SST2;
DJF and FMA SST1 and SST2;
April SOI;
February and April SOI;
FMA SOI; and
DJF and FMA SOI.

This represents a total of 16 possible forecast systems for each of the six stations, i.e. there are four systems using the SOI (with the SOI in different as predictor), four using just SST1, four using SST2, and four systems using both SST1 and SST2.

Table 4 lists the number of times that a positive LEPS score was obtained from these various systems, categorised according to whether the SOI, SST1 only, SST2 only, or both SST1 and SST2, were used. The LEPS scores were below 10 in all cases, with the highest LEPS score of 7.73 for Manjimup using the DJF and FMA SOI values.

Table 4: Winter Rainfall: Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	2	1	2	1
Jarrahdale	3	0	1	3
Lake Grace	2	0	1	2
Merredin	0	0	0	0
Manjimup	4	1	2	4
Kalgoorlie	1	1	1	1

The skill of the forecast systems was also examined using the first differences of all the data (i.e., the rainfall, SST and SOI data series). The results are summarised in Table 5. The number of skilful rainfall forecasts for Mingenew increased when the data were differenced, while for Manjimup the number tended to decrease. As was the case with the “raw”, undifferenced data, there were no LEPS scores over 10. The highest score was 5.47, for Mingenew using DJF and FMA SSTs 1 and 2.

The question of whether these forecasts could be improved by using May, April and May (MAM), or JFM and MAM SSTs or SOI values, was then addressed. The results for the raw data are listed in Table 6, while Table 7 lists the results for the first differenced data. Comparing Tables 4 and 6 indicates that there are some improvements in skill when using the later data in the forecasts (Table 6). This is also the case for the differenced data (compare Tables 5 and 7). With the later data used in the forecast we get the first LEPS score over 10 (11.48 for Manjimup using May SST1 and 2 values). The LEPS scores for the differenced data were generally lower than for the raw data.

Table 5: Differenced Winter Rainfall: Number of positive LEPS scores obtained for first differenced data. A maximum of four is possible in each of the grid cells.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	4	1	4	0
Jarrahdale	2	3	2	0
Lake Grace	1	0	0	1
Merredin	0	2	2	2
Manjimup	0	2	0	0
Kalgoorlie	0	2	1	1

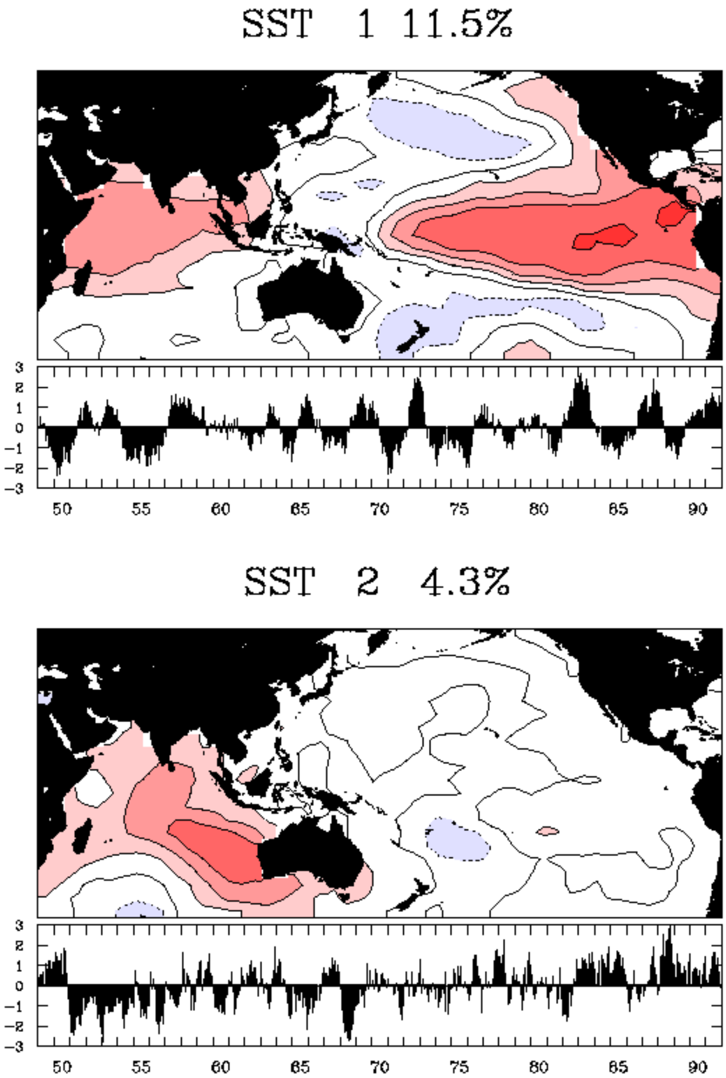

Figure 1. **First two VARIMAX rotated empirical orthogonal functions (EOFs) of the standardised monthly anomalies of the sea surface temperature data (Drosdowsky and Chambers, 1998).**

Table 6: Winter Rainfall using later predictors: Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	2	0	0	4
Jarrahdale	4	0	3	4
Lake Grace	4	0	2	4
Merredin	2	0	0	0
Manjimup	3	2	2	1
Kalgoorlie	1	1	1	1

Table 7: Differenced Winter Rainfall using later predictors: Number of positive LEPS scores obtained for first differenced data. A maximum of four is possible in each of the grid cells, except for SST1&2 where only three combinations were possible.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	4	3	1	1
Jarrahdale	0	1	0	0
Lake Grace	0	2	1	3
Merredin	0	1	0	1
Manjimup	0	1	1	1
Kalgoorlie	4	0	2	0

No predictor set gave positive LEPS scores for all six stations. Overall, the performance of the linear forecast techniques on winter rainfall was poor, with little evidence that useful forecasts would be obtainable.

Spring (September to November)

Rainfall

A similar analysis to that outlined above was carried out for spring (September to November) rainfall. Four groups of analyses were considered. These used predictors available at the end of May, June or July, or used differenced data with predictors ending in July. Tables 8 to 10 indicate that the prediction of spring rainfall was generally more skillful when using data from up until the end of July rather than relying only on the earlier (May or June) predictors. However, the skill levels in all cases were fairly low with very few cases of LEPS scores over 10. The 'best' predictor overall, when using data until the end of July, was (marginally) SST1. However, if Mingenew and Kalgoorlie are excluded, then the SOI is also a potentially useful predictor. For most stations, using differenced data tended to either reduce the skill of the predictions, or have little effect (Merredin and Kalgoorlie).

Table 8: Spring rainfall (predictors until end of May): Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells (i.e., using either May, March and May, MAM, or JFM and MAM, as predictors). The number of LEPS scores greater than 10 are given in brackets.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	0 (0)	2 (0)	1 (0)	0 (0)
Jarrahdale	4 (0)	4 (0)	4 (0)	3 (0)
Lake Grace	2 (0)	4 (0)	4 (0)	4 (0)
Merredin	0 (0)	0 (0)	0 (0)	4 (0)
Manjimup	4 (1)	1 (0)	4 (1)	4 (0)
Kalgoorlie	1 (0)	0 (0)	0 (0)	0 (0)

Table 9: Spring rainfall (predictors until end of June): Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells (June, April and June, AMJ, FMA and AMJ). There were no LEPS scores greater than 10.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	0	3	2	0
Jarrahdale	4	4	4	4
Lake Grace	3	3	4	3
Merredin	1	0	0	3
Manjimup	4	1	4	4
Kalgoorlie	0	0	0	1

Table 10: Spring rainfall (predictors until end of July): Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells (July, May and July, MJJ, MAM and MJJ). The number of LEPS scores greater than 10 are given in brackets.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	2 (0)	2 (0)	4 (0)	0 (0)
Jarrahdale	4 (0)	4 (0)	4 (0)	4 (0)
Lake Grace	2 (0)	4 (0)	4 (0)	4 (0)
Merredin	2 (0)	0 (0)	0 (0)	3 (0)
Manjimup	4 (1)	3 (0)	4 (1)	4 (0)
Kalgoorlie	1 (0)	1 (0)	1 (0)	0 (0)

Table 11: Differenced Spring Rainfall (predictors until end of July): Number of positive LEPS scores obtained for first differenced data. A maximum of four is possible in each of the grid cells, except for SST1&2 where there were only three possible combinations. There were no LEPS scores over 10.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	1	1	1	2
Jarrahdale	2	3	2	1
Lake Grace	4	2	3	2
Merredin	2	0	1	3
Manjimup	3	0	1	2
Kalgoorlie	1	1	0	3

Temperature

Forecast systems for mean temperature, and for mean maximum and mean minimum temperatures for spring (September to November) were tested. As spring rainfall was best predicted using data until the end of July, spring temperature predictions were only tested with systems using data available up to the end of July (rather than only using earlier data). SST1&2 gave the highest LEPS scores for spring mean temperature, though SOI and SST1 also performed fairly well (Table 12).

Table 12: Spring mean temperature: Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells. The number of LEPS scores greater than 10 are given in brackets.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	4 (0)	0 (0)	3 (0)	4 (0)
Jarrahdale	4 (4)	4 (4)	4 (4)	4 (2)
Lake Grace	4 (0)	2 (0)	4 (0)	4 (0)
Merredin	4 (3)	4 (0)	4 (4)	4 (4)
Manjimup	4 (0)	4 (0)	4 (0)	4 (4)
Kalgoorlie	4 (0)	4 (0)	4 (0)	4 (0)

The SOI was the ‘best’ predictor of spring mean maximum temperature (Table 13), though no method worked particularly well for Manjimup. SST2 was the clearly the worst potential predictor of spring mean maximum temperature. No methods worked particularly well for Manjimup.

Table 13: Spring mean maximum temperature: Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells. The number of LEPS scores greater than 10 are given in brackets.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	4 (0)	0 (0)	4 (0)	4 (0)
Jarrahdale	4 (2)	1 (0)	3 (1)	4 (2)
Lake Grace	4 (0)	0 (0)	4 (0)	4 (1)
Merredin	4 (2)	0 (0)	4 (0)	4 (3)
Manjimup	1 (0)	0 (0)	0 (0)	1 (0)
Kalgoorlie	2 (0)	2 (0)	2 (0)	4 (0)

The most consistently skilful system, over all stations, of spring mean minimum temperature (Table 14) used both SST 1&2, however SST1, SST2, and the SOI also performed relatively well for most stations. The LEPS scores associated with prediction of mean minimum temperature were generally higher than those for mean spring temperature, and much greater than those for mean maximum temperature. The results of using differenced spring mean minimum temperatures are in Table 15. When differenced data were used the resulting LEPS scores were considerably lower than for the raw data (except for Mingenew using SST2). This is particularly evident when using SST1 or SST1&2.

Table 14: Spring mean minimum temperature: Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells. The number of LEPS scores greater than 10 are given in brackets.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	4 (0)	0 (0)	4 (0)	4 (0)
Jarrahdale	4 (0)	4 (4)	4 (4)	4 (1)
Lake Grace	4 (0)	4 (4)	4 (4)	4 (1)
Merredin	4 (0)	4 (4)	4 (4)	4 (4)
Manjimup	4 (4)	4 (0)	4 (4)	4 (4)
Kalgoorlie	4 (0)	4 (0)	4 (0)	4 (0)

Table 15: Spring mean minimum temperature: Number of positive LEPS scores obtained for first differenced data. A maximum of four is possible in each of the grid cells.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	2	4	3	3
Jarrahdale	0	2	0	2
Lake Grace	0	3	1	4
Merredin	0	4	3	4
Manjimup	0	4	3	4
Kalgoorlie	0	4	2	2

Summer (December to February)

Rainfall

A similar analysis was carried out for summer (December to February) rainfall. Here September, July and September, averaged July to September (JAS), and averaged May to July (MJJ) and JAS SST and SOI data were used to forecast the rainfall. The results for the raw data are given in Table 16 and for the first differenced data in Table 17.

From Table 16 it is clear that the SST forecast system tends to perform better than the SOI based system for summer rainfall. Comparing Tables 4, 6, 10 and 16 it is also apparent that forecasts of summer rainfall have generally higher LEPS scores than those for winter and spring, with a number of LEPS scores over 10. There are now four combinations of predictors that give positive LEPS scores for all six stations: September SSTs 1 and 2; JAS SSTs 1 and 2; MJJ and JAS SST1 only; and MJJ and JAS SSTs 1 and 2.

When the differenced data were used the LEPS scores were greatly reduced with no LEPS scores over 8 and many negative scores (Table 17). No set of (differenced) predictors gave positive LEPS scores for all six stations.

Table 16: Summer rainfall: Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells. The number of LEPS scores greater than 10 are given in brackets.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	4 (0)	4 (0)	4 (4)	2 (0)
Jarrahdale	4 (0)	4 (0)	4 (0)	1 (0)
Lake Grace	4 (3)	0 (0)	4 (3)	4 (0)
Merredin	3 (0)	4 (0)	4 (3)	0 (0)
Manjimup	1 (0)	4 (0)	3 (0)	0 (0)
Kalgoorlie	4 (0)	1 (0)	4 (0)	1 (0)

Table 17: Summer rainfall: Number of positive LEPS scores obtained for first differenced data. A maximum of four is possible in each of the grid cells, except for SST1&2 where only three combinations were possible. There were no LEPS scores over 10.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	0	2	1	0
Jarrahdale	0	1	0	2
Lake Grace	1	0	0	0
Merredin	0	1	0	1
Manjimup	0	2	1	1
Kalgoorlie	0	1	0	1

Mean Maximum Temperature

Using the same set of predictors as for summer rainfall the average maximum summer (DJF) temperature was forecast and the skill assessed using LEPS scores. The results are given in Table 18 (raw data) and Table 19 (differenced data).

Table 18: Summer mean maximum temperature: Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells. The number of LEPS scores greater than 10 are given in brackets.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	1 (0)	2 (0)	3 (0)	2 (0)
Jarrahdale	4 (1)	0 (0)	3 (1)	2 (0)
Lake Grace	4 (0)	2 (0)	4 (0)	3 (0)
Merredin	4 (0)	0 (0)	4 (0)	4 (0)
Manjimup	1 (0)	4 (1)	4 (2)	0 (0)
Kalgoorlie	2 (0)	0 (0)	0 (0)	1 (0)

Only one set of predictors gave positive LEPS scores for all stations: JAS SST 1 only, though all the LEPS scores were less than 5. When differenced the SST forecast schemes generally gave lower LEPS scores than the SOI based schemes. The only differenced scheme to give positive LEPS scores at all six stations (one over 10) was MJJ and JAS SOI.

Table 19: Summer mean maximum temperature: Number of positive LEPS scores obtained for first differenced data. A maximum of four is possible in each of the grid cells, except for SST1&2 where only three combinations were possible.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	1	2	0	1
Jarrahdale	0	0	0	2
Lake Grace	0	0	0	1
Merredin	0	2	0	3
Manjimup	0	0	0	4 (2)
Kalgoorlie	0	2	1	2

Number of days over 35°C

Forecasts of the number of days over 35°C were made using the same predictors as for summer rainfall. The results are given in Table 20. Merredin and Manjimup are the 'best' forecast stations with positive LEPS scores regardless of the predictors used. The only predictor to give positive LEPS scores for all six stations was JAS SST1.

Table 20: Number of days over 35°C: Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells. The number of LEPS scores greater than 10 are given in brackets.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	4	0	4	2
Jarrahdale	2	0	2	2
Lake Grace	2	0	0	1
Merredin	4	4	4	4
Manjimup	4	4	4 (2)	4
Kalgoorlie	2	0	0	4

Number of days over 40°C

Forecasts of the number of days over 40°C were made using the same predictors as for summer rainfall (Table 21). No forecasts were possible for Jarrahdale and Lake Grace. Only Kalgoorlie (using SSTs 1 and 2) had LEPS scores over 10. Except for Kalgoorlie, the LEPS scores for forecasts of the number of days over 40°C were generally lower than for forecasts of the number of days over 35°C.

Table 21: Number of days over 40°C: Number of positive LEPS scores obtained. A maximum of four is possible in each of the grid cells. The number of LEPS scores greater than 10 are given in brackets.

Station Name	SST1	SST2	SST1&2	SOI
Mingenew	1	0	0	2
Merredin	0	1	0	0
Manjimup	1	3	1	0
Kalgoorlie	4	2	4 (2)	4

Summary

Overall the results presented above are mixed.

There does appear to be some skill in predicting summer rainfall, summer mean maximum temperature, and extreme temperature events (such as the number of days over 35°C). In general, for the raw data, predictions using SST1 only or SST1 and SST2 together tended to give more consistently positive LEPS scores than those using SST2 only or the SOI. However, when the original data were differenced the SOI and SST2 only tended to give better results.

For winter rainfall, the LEPS scores tended to be lower than for summer rainfall and temperature forecasts. There were mixed results with forecasts for Mingenew showing some skill both in the raw and differenced data. The stations selected in this analysis differ in their yearly rainfall distributions with Mingenew and Kalgoorlie having less peaked winter rainfall maxima. This may mean that different predictors could be needed for Mingenew and Kalgoorlie than for the other stations.

The skill obtainable for spring rainfall predictions lies between that of summer and winter rainfall. In order of increasing overall skill, the spring predictions were rainfall, mean maximum temperature, mean temperature and mean minimum temperature, with the temperature forecasts tending to have considerably greater skill than the rainfall forecasts. There appears to be some skill in predicting spring temperatures, and to some extent rainfall, using data up to the end of July.

A few representative illustrations of the strength of the better relationships are shown in Figures 2-5. The degree to which the symbols for the three terciles are separated in the figures indicates the strength of the predictive relationships.

The first example (Figure 2) shows the prediction of September-November rainfall using May-July values of the SST predictors. This example has a moderate LEPS score and there is considerable separation of the tercile symbols, suggesting a potentially useful level of skill.

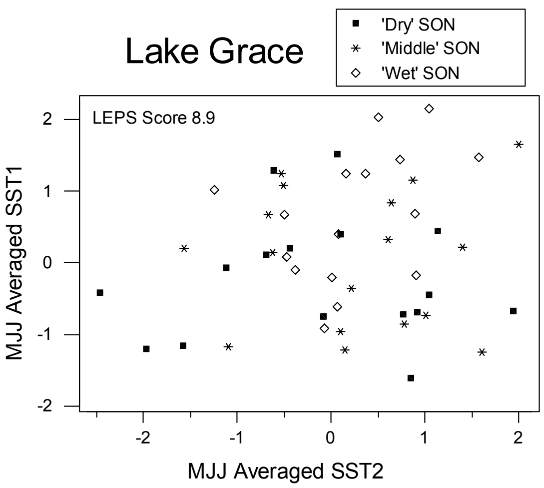

Figure 2: Lake Grace September-November rainfall versus May-July SST patterns

Figure 3 illustrates that summer rainfall exhibits some predictability, with most wet summers at Manjimup being preceded by negative values of SST1 in July-September, i.e., La Niña episodes. One of the higher values of LEPS scores, 21.6, is illustrated in Figure 4, which shows that September-November mean minimum temperature at Jarrahdale appears to be strongly related to values of the SST patterns in May-July. Finally, extreme summer temperatures, as measured by the number of days with maximum temperatures exceeding 35ºC at Lake Grace, seem to be predictable using July-September SST patterns (Figure 5).

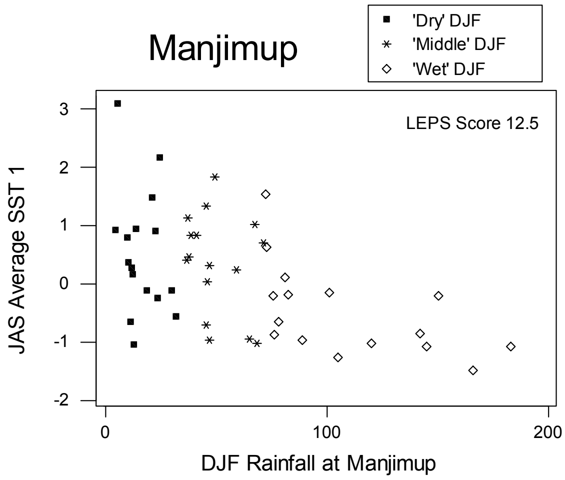

Figure 3: Manjimup summer rainfall versus July-September SST1

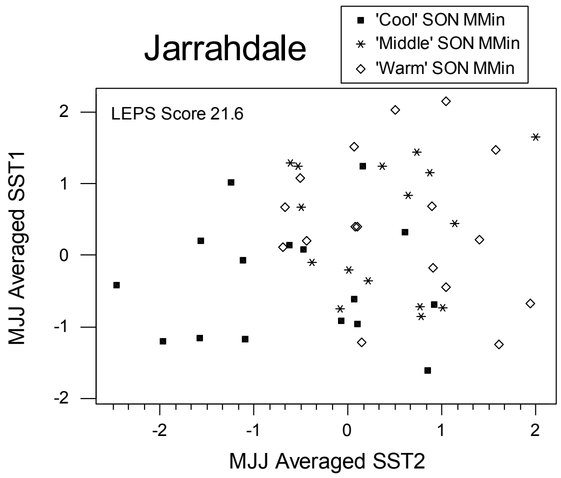

Figure 4: Jarrahdale September-November mean minimum temperature versus SST1 & SST2 in May-July

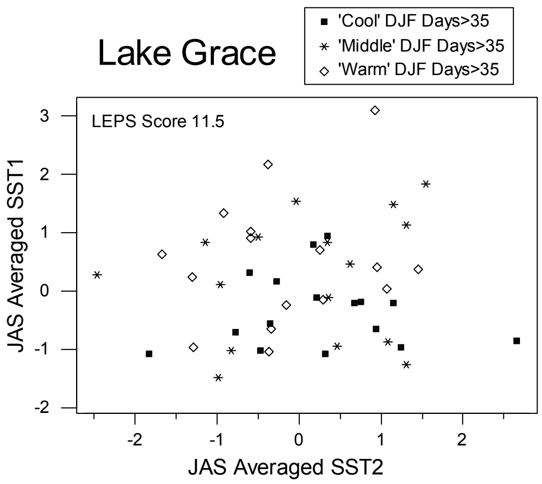

Figure 5: Number of days at Lake Grace in December-February with maximum temperatures exceeding 35C, versus SST patterns in July-September

Sea Surface Temperature Gradients and Prediction

Some preliminary work suggested that SST gradients in the Indian Ocean might be of use in predicting SWWA rainfall, especially during winter (May-October). A comprehensive study of this possibility was undertaken, in an attempt to determine if other SST predictors other than SST1 and SST2 could provide useful predictive information.

Rainfall and Temperature Data

May to October rainfall totals and averaged May to October temperature data were available for Mingenew, Jarrahdale, Manjimup, Merredin, Lake Grace and Kalgoorlie.

SST Data

We used 2-degree reconstructed near-global SST (NCEP) data from the period 1950 to 1998. This data was then averaged to produce a 4° x 4° gridded data set, covering latitudes 44° S to 68° N. Temperature gradients were obtained by calculating the latitudinal change in temperature from one grid box to the next.

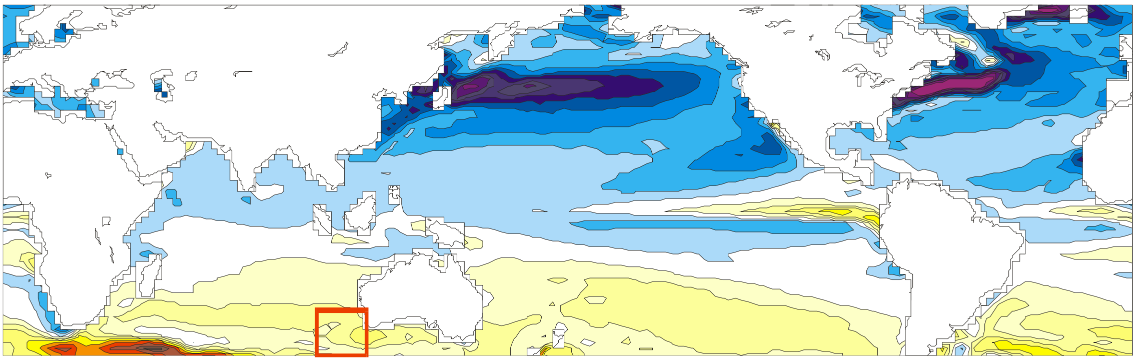

Figure 6. Averaged May to October SST gradients (1950 to 1998). The red box shows the location of the 9 gradient boxes (each 4° latitude x 4° longitude) mentioned in the text.

Correlations of SST Gradients with SW Rainfall

A group of nine SST gradient grid boxes, covering the region 29° to 41° S and 104° to 116° E, were selected as potential SWWA rainfall and temperature predictors (see Figure 6). The selection of these boxes was based on unpublished work by Dr. D. A. Jones who found that an SST gradient box within this region was highly correlated with winter rainfall at Manjimup during the period 1982 to 1994. The relationship was less strong when longer time periods were used, indicating a possible change in the relationship between rainfall and SST gradients in the SWWA area may have occurred sometime prior to 1982.

When a similar analysis was carried out using the SST gradients described above, two of the nine SST gradient boxes indicated possible predictive skill for Manjimup winter rainfall, particularly when only using more recent years. Table 22 lists the correlations (and significance levels) for two of the gradient boxes. Table 22 indicates that a change in the relationship between the SST gradients and Manjimup rainfall most likely occurred prior to 1965. The relationship is shown graphically in Figure 7.

Table 22.Simultaneous correlation of SST gradient boxes with Manjimup May to October rainfall. Box 3 is centred on 106°E, 31°S and Box 8 on 114°E, 35°S. The p-values for the correlation coefficients are given in brackets.

Period	Box 3	Box 8
1950-1998	0.148 (0.311)	0.050 (0.736)
1965-1998	0.429 (0.011)	0.377 (0.028)
1982-1998	0.812 (0.000)	0.583 (0.018)

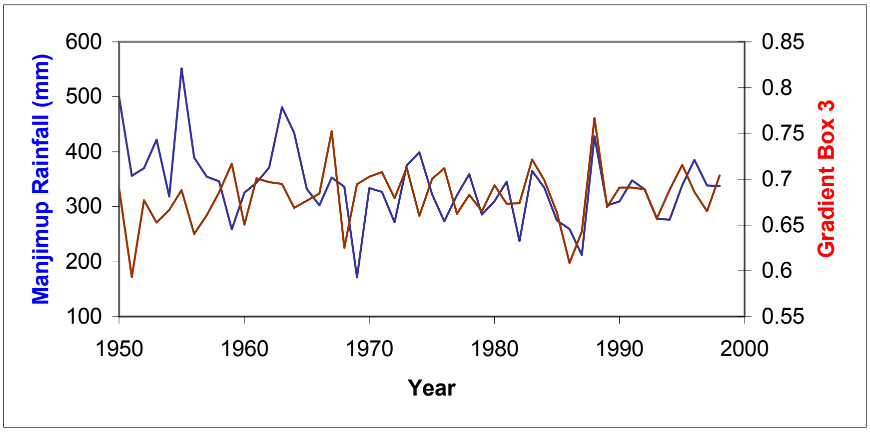

Figure 7. Graphical illustration of the relationship between SST gradient in Box 3 and Manjimup May to October rainfall.

Rainfall Tercile Prediction Using SST Gradients

When the full data set (1950 to 1998) is used to assess the potential to predict May to October rainfall from SST Gradients no significant skill is obtained.

If data from the period 1965 to 1998 only is used, marginally skilful rainfall predictions were possible for Manjimup using a single months SST gradient (Box 3; from February to May) with slight increases in skill achievable if three month averaged SST gradients are used (see Table 23). No significant skill was achieved for the other five rainfall stations.

Although the number of years in the period 1982 to 1998 is relatively small, the skill of rainfall predictions, using SST gradients for Boxes 3 and 8 was assessed with the results given in Tables 24 and 25. For brevity only the results for the single month gradients are given with generally no improvement in skill being obtained using three-month average gradients.

Table 23.LEPS skill scores for prediction of Manjimup May to October rainfall using Box 3 (centred on 106°E, 31°S) SST gradients. Data used is 1965 to 1998.

Gradient Month	LEPS Score	Gradient Months	LEPS Score
Jan	-1.21	11-1	3.54
Feb	4.01	12-2	4.95
Mar	1.28	1-3	4.30
Apr	5.43	2-4	8.11
May	3.19	3-5	6.23

Gradient Box 3 appears to provide the best predictions of May to October rainfall, particularly for Manjimup, with some moderate skill at Mingenew, Jarrahdale and Lake Grace in April and May. Forecasts using May gradient values however, are of little use as there is no lead-time.

Table 24.LEPS skill scores for the prediction of May to October rainfall using Box 3 (centred on 106°E, 31°S) SST gradients. Data used is 1982 to 1998.

Gradient Month	Mingenew	Jarrahdale	Manjimup	Merredin	Lake Grace	Kalgoorlie
Jan	-5.53	-5.92	-7.20	7.23	1.87	2.52
Feb	-6.40	-6.73	4.19	-4.89	-5.95	-7.99
Mar	2.16	-4.75	4.49	3.81	-2.73	-6.89
Apr	6.21	4.96	18.65	-1.07	2.14	-2.76
May	4.64	12.53	19.68	-6.56	15.42	-7.58

Table 25.LEPS skill scores for the prediction of May to October rainfall using Box 8 (centred on 114°E, 35°S) SST gradients. Data used is 1982 to 1998.

Gradient Month	Mingenew	Jarrahdale	Manjimu p	Merredin	Lake Grace	Kalgoorlie
Jan	-5.00	-6.44	-6.64	-4.08	-3.85	-6.18
Feb	-7.18	-4.11	-2.85	-4.76	-6.84	-2.99
Mar	-7.28	-4.02	-4.08	8.72	16.23	-3.41
Apr	-0.69	-3.32	5.20	-5.72	-4.38	-3.62
May	-0.99	-1.63	6.28	-2.92	-7.39	-7.76

Temperature Tercile Prediction Using SST Gradients

As for rainfall the potential predictability of temperature variables using SST gradients was first tested using the full data set (1950 to 1998). Simultaneous correlations for two of the nine SST gradient boxes are given in Table 26. Gradient

Box 3 generally gave the highest correlation values with significant correlations for all six temperature stations. Gradient Box 9 (results not shown) had significant correlations with all six temperature stations, however the values were generally lower than those for Box 3. As an example, the relationship between SST gradient Box 3 and Lake Grace May to October mean temperature is graphically illustrated in Figure 8.

Table 26.Simultaneous correlation of SST gradient boxes with station May to October mean temperature (1950 – 1998). Box 3 is centred on 106°E, 31°S and Box 8 on 114°E, 35°S. The p-values for the correlation coefficients are given in brackets.

Station	Box 3	Box 8
Mingenew	0.385 (0.006)	0.266 (0.065)
Jarrahdale	0.487 (0.000)	0.371 (0.009)
Manjimup	0.375 (0.008)	0.197 (0.175)
Merredin	0.467 (0.001)	0.342 (0.016)
Lake Grace	0.467 (0.001)	0.281 (0.050)
Kalgoorlie	0.501 (0.000)	0.306 (0.032)

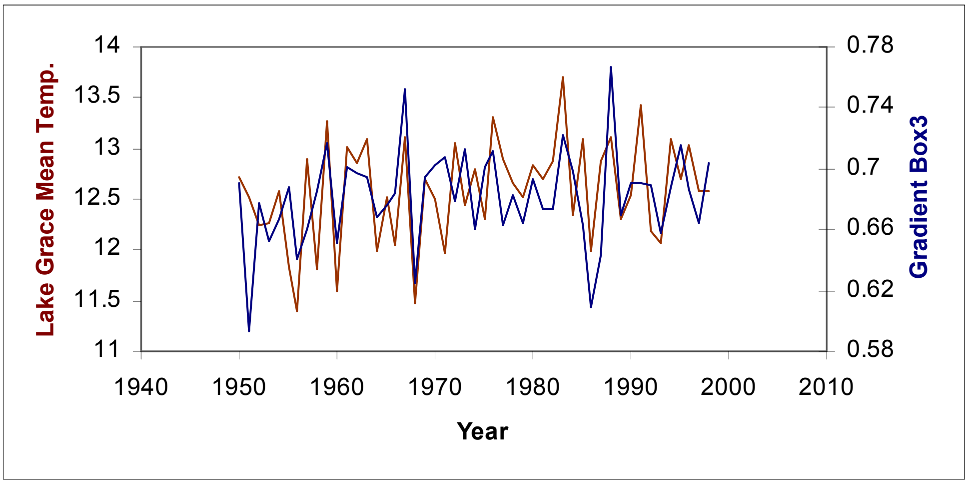

Figure 8. May to October Lake Grace mean temperature and May to October SST gradient Box 3.

Table 27.LEPS skill scores for the prediction of May to October mean temperature, using SST gradient Box 3. Data used is 1950 to 1998. Similar results were obtained when using three-month averaged SST gradients.

Gradient Month	Mingenew	Jarrahdale	Manjimup	Merredin	Lake Grace	Kalgoorlie
Jan	-2.00	-1.63	-2.17	-1.99	-1.99	0.31
Feb	-1.83	-2.00	-1.34	0.28	-1.21	-1.42
Mar	5.38	1.66	0.77	0.67	2.53	2.03
Apr	2.04	2.01	-0.98	4.55	0.95	1.27
May	4.62	0.90	-1.44	0.43	-1.88	3.70

Although generally high correlation values were found for simultaneous May to October mean temperature and SST gradient Box 3 the predictive ability of SST gradient Box 3 was not high (Table 27). Unlike the case with rainfall (see Figure 3) there were no obvious changes in the relationship between the SST gradients and mean temperature (see Figure 8). Therefore analyses were not carried out for shorter time periods.

Summary

Overall, the results of these tests of the use of SST gradients in winter prediction were somewhat disappointing. There was little evidence that the gradients could produce useful temperature forecasts. There was some evidence that winter rainfall predictions might be possible. However, this was only so using recent data – the earlier data showed no predictive relationship. This may suggest that earlier data were of poor quality. Retesting with future data will be required to confirm whether the recent predictability is real.

Wheat yield predictability

The most disappointing result from the above studies was the low skill apparently achievable for predicting winter rainfall, using either the SOI or SST patterns. Winter rainfall is clearly of importance for agricultural purposes, so it appears that the chances of forecasting crop yields are low. Nevertheless, a preliminary examination of the predictability of wheat yields was undertaken, for the shire of Yilgarn.

Data

A long term data set of shire-level wheat yields for the shire of Yilgarn (of which Southern Cross is a major town) was provided by D. Stephens of Agriculture Western Australia. These data were based on Australian Bureau of Statistics (ABS) census data from 1930 to 1996 and a sample survey (not a full census) for 1997. This data set had not been adjusted for advances in farming techniques so a simple linear regression against year was used to adjust the yields over the period 1950 to 1997. The raw and adjusted yields are shown in Figure 9. The period 1950 to 1997 was chosen as it overlaps with the other data sets mentioned below.

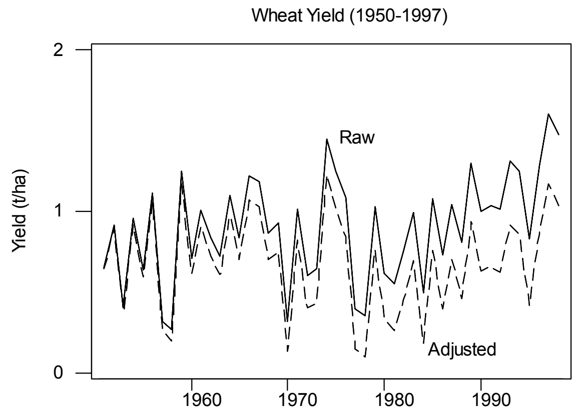

Figure 9. Raw and adjusted wheat yields for Yilgarn shire, 1950 to 1997.

High-quality monthly rainfall data were available from Kalgoorlie to the east of Southern Cross, and from Merredin to the west of Southern Cross. The period of rainfall records used in this study was 1949 to 1997. Monthly temperature data (mean minimum, mean maximum and diurnal temperature range or DTR) were also available at Merredin and Kalgoorlie.

Method

A statistical forecast scheme, similar to that used above for prediction of rainfall and temperature, was adopted for wheat yield prediction. Lagged values of the predictor variables time series (rainfall at Kalgoorlie, SST time score series, SOI) are used to forecast the probability of the wheat yield in pre-defined categories. In this study predictions were made for both wheat yield terciles (three equally probable categories) and medians (two equally probable categories).

Results

Table 28 lists the skill scores for tercile forecasts of wheat yield. Only months one to ten (January to October) are used to forecast the yield. It is evident from Table 1 that skilful prediction of wheat yield using SST1, SST2, SST1 and SST2 or the SOI is unlikely. A similar analysis using 3-month averaged SST and SOI values, with the average ending in month m, was also conducted but resulted in skill scores similar to those in Table 28.

Table 28.LEPS skill scores for wheat yields (terciles). The predictor month used to forecast the yield is given in brackets. For example, the first row of data is for January (m=1) and predictors using (m, m-2) use January and November (of the previous year).

Month	SST1(m)	SST2(m)	SST1&2(m)	SST1(m,m-2)	SST2(m,m-2)	SST1&2(m,m-2)	SOI(m)	SOI(m,m-2)
1	-2.05	-2.80	-5.02	-2.10	-3.81	-6.79	-2.51	-4.04
2	-1.23	-0.79	-2.19	-0.80	-2.36	-3.19	-2.45	-4.76
3	-0.16	1.45	1.01	-1.42	1.81	0.40	-1.52	-3.86
4	-0.98	-1.91	-2.92	-3.11	-2.79	-6.88	-1.16	-3.30
5	-1.40	-2.05	-3.25	-2.01	0.04	-2.24	-1.43	-2.64
6	-1.15	-1.97	-2.54	-3.50	-3.89	-7.10	-0.98	-3.38
7	0.26	-1.28	0.61	1.68	-2.71	-0.24	2.49	5.02
8	-0.82	1.68	1.88	-2.42	2.99	2.26	-1.43	-1.97
9	-2.00	-1.32	-2.64	0.88	-3.83	-0.09	0.25	0.78
10	-2.17	0.05	-1.66	2.69	-0.62	0.72	-1.62	-0.98

The skill scores for above and below median wheat yield forecasts are given in Table 29. When forecasting two categories of wheat yield there is more skill, in most months, than when forecasting for three categories. However the most skilful predictions are very late in the year (August and October) making their usefulness to wheat producers limited. Again, the analysis using three-month averaged SST and SOI values gave similar results, though no months had skill scores over 10. A subset of these results is illustrated graphically in Figure 10.

Table 29.LEPS skill scores for wheat yields (above/below median). The predictor month used to forecast the yield is given in brackets. For example, the first row of data is for January (m=1) and predictors using (m, m-2) use January and November (of the previous year).

Month	SST1(m)	SST2(m)	SST1&2(m)	SST1(m,m-2)	SST2(m,m-2)	SST1&2(m,m-2)	SOI(m)	SOI(m,m-2)
1	-1.61	-2.27	-3.95	0.62	-4.48	-3.66	-0.81	-3.05
2	-0.77	-1.70	-2.48	-2.40	-3.92	-6.77	-1.85	-3.51
3	-1.76	1.82	0.42	-3.86	3.82	2.04	-2.21	-2.46
4	-1.74	-1.63	-3.42	-2.55	-3.90	-5.95	-2.18	-4.03
5	-1.76	2.23	-3.25	0.10	0.43	2.40	-2.19	-4.49
6	-1.94	-0.32	-2.38	-0.24	-2.46	-1.41	-1.53	-3.48
7	-2.08	2.93	0.84	-1.58	0.84	-1.95	3.28	5.10
8	-2.18	11.07	8.87	-4.13	13.44	10.11	2.33	0.59
9	-1.73	5.89	3.96	0.06	3.78	5.34	5.05	3.09
10	0.13	2.45	2.05	5.45	9.66	10.47	-2.12	3.97

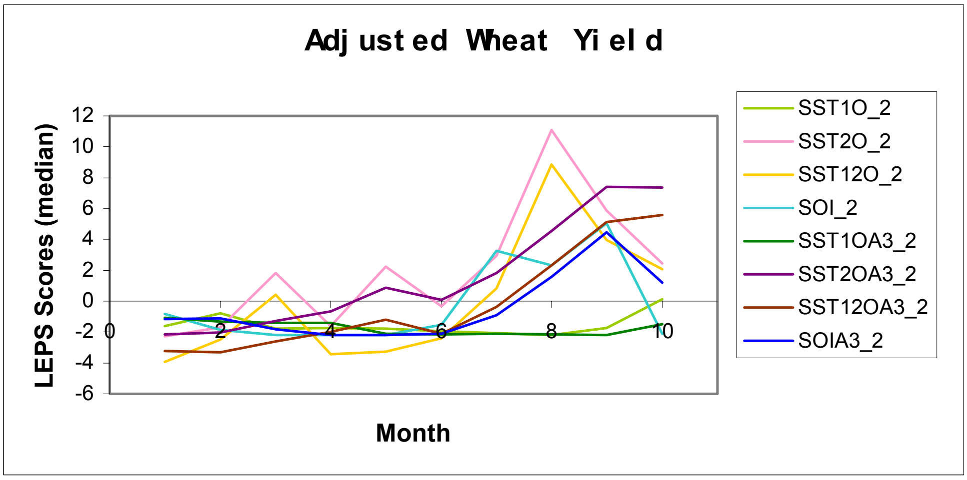

Figure 10. LEPS skill scores for forecasts of median wheat yield at Yilgarn by month. SST1O_2 uses SST1 in month m; SST2O_2 uses SST2 in month m; SST12O_2 uses SST1 and SST2 in month m; SOI_2 uses the SOI in month m; SST1OA3_2 uses three-month averaged SST1 values ending in month m; SST2OA3_2 uses three-month averaged SST2 values ending in month m; SST12OA3_2 used SST1 and SST2 three-month averaged values ending in month m; and SOIA3_2 uses three-month averaged SOI values ending in month m.

Table 30 lists the results for forecasts of tercile Yilgarn wheat yields using rainfall from Kalgoorlie and Merredin. The results for above/below median forecasts were similar. Forecasts using rainfall (either from Kalgoorlie or from Merredin) tend to have higher skill scores than those made using the SSTs or the SOI. In particular, when rainfall is used as a predictor skilful forecasts appear to be possible as early as April. The results from Table 30 are shown graphically in Figure 11.

Table 30.LEPS skill scores for Yilgarn wheat yields (terciles) using Kalgoorlie or Merredin rainfall. The predictor month used to forecast the yield is given in brackets. For example, the first row of data is for January (m=1) and predictors using (m, m-2) use January and November (of the previous year). Kal = Kalgoorlie, Mer = Merredin.

Month	Kal (m)	Mer (m)	Kal (m,m-2)	Mer (m,m-2)	Kal (3m)	Mer (3m)	Kal (3m,3m-1)	Mer (3m,3m-1)
1	-1.74	1.77	-3.72	3.20	-0.56	-1.15	-0.97	2.57
2	5.87	1.27	5.68	1.94	4.23	4.48	2.69	4.16
3	12.05	-1.27	10.58	0.73	10.92	2.30	12.69	0.45
4	30.29	12.73	31.21	12.21	22.21	8.97	23.66	8.95
5	-0.39	1.99	11.10	0.44	27.10	9.29	28.92	9.43
6	3.00	2.35	30.42	15.04	18.63	13.89	35.43	17.97
7	6.86	15.26	6.19	15.51	9.88	17.78	26.54	17.44
8	3.02	4.00	5.34	6.35	13.82	25.70	19.11	27.40
9	4.57	3.09	11.36	15.46	15.24	24.76	19.45	33.61
10	-1.21	-1.21	0.87	3.85	5.69	7.94	14.78	27.25

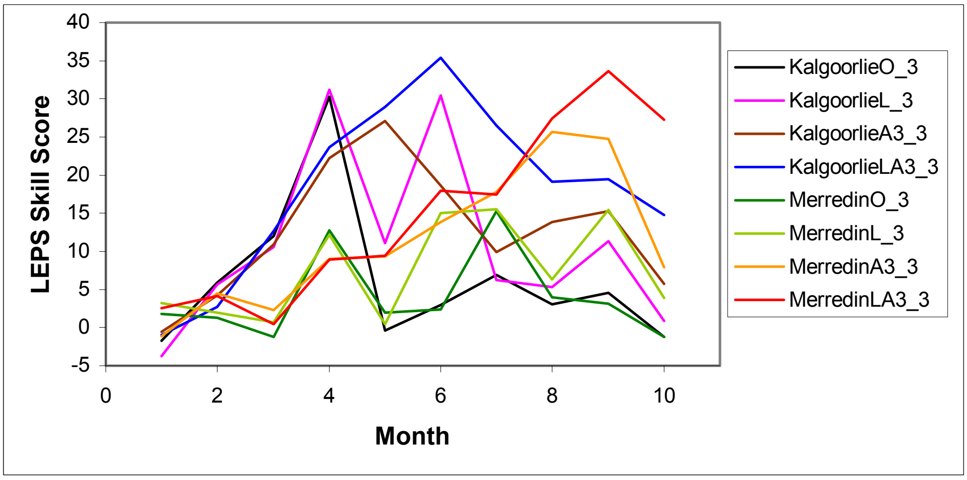

Figure 11. LEPS skill scores for forecasts of median wheat yield at Yilgarn by month using rainfall at Kalgoorlie or Merredin as predictors. The legend is as in Figure 6.

Table 31 lists the results for forecasts of tercile Yilgarn wheat yields using mean minimum monthly temperatures at Kalgoorlie and Merredin. Although not shown, the results for above/below median forecasts gave generally higher skill levels than for terciles, for example above/below median yield forecasts using Kalgoorlie (m,m-2) minimum temperatures had skill scores ranging from 4.47 to 14.85 when m was between 7 and 10. However, forecasts this late in the year are unlikely to provide useful information to farmers.

Table 31.LEPS skill scores for Yilgarn wheat yields (terciles) using Kalgoorlie or Merredin monthly mean minimum temperatures. The predictor month used to forecast the yield is given in brackets. For example, the first row of data is for January (m=1) and predictors using (m, m-2) use January and November (of the previous year). Kal = Kalgoorlie, Mer = Merredin.

Month	Kal (m)	Mer (m)	Kal (m,m-2)	Mer (m,m-2)	Kal (3m)	Mer (3m)	Kal (3m,3m-1)	Mer (3m,3m-1)
1	-0.38	-2.16	-2.18	-3.38	-2.22	-2.10	-0.20	-4.00
2	-2.15	-2.05	-4.77	-4.50	-2.56	-2.27	-2.98	-3.61
3	-2.34	-1.88	-2.23	-4.07	-2.36	-2.17	-4.73	-4.10
4	1.00	-0.02	-0.90	-2.60	-0.14	-0.71	-2.07	-3.33
5	0.00	-1.82	-2.02	-3.44	0.13	-1.41	-1.32	-3.44
6	-1.48	-2.09	-0.49	-2.16	1.41	-1.56	0.02	-2.76
7	3.91	1.31	3.36	-0.10	3.11	-1.24	1.22	-3.00
8	1.63	-0.56	0.04	-2.45	-1.85	-2.17	-0.31	-2.77
9	1.11	1.34	4.49	3.74	-1.77	-1.73	4.51	-0.99
10	-0.10	1.56	0.31	0.01	2.87	2.53	3.27	4.14

Table 32 lists the results for forecasts of tercile Yilgarn wheat yields using mean maximum monthly temperatures at Kalgoorlie and Merredin. Potentially useful skill levels were achieved when using three-month averages of maximum monthly temperatures for both Merredin and Kalgoorlie. The skill levels were generally greater in the latter months (after May). Mean monthly maximum temperatures at Kalgoorlie (three month average no lags) tended to provide more consistently high skill levels than the other combinations presented in Table 32.

Table 32.LEPS skill scores for Yilgarn wheat yields (terciles) using Kalgoorlie or Merredin monthly mean maximum temperatures. The predictor month used to forecast the yield is given in brackets. For example, the first row of data is for January (m=1) and predictors using (m, m-2) use January and November (of the previous year). Kal = Kalgoorlie, Mer = Merredin.

Month	Kal (m)	Mer (m)	Kal (m,m-2)	Mer (m,m-2)	Kal (3m)	Mer (3m)	Kal (3m,3m-1)	Mer (3m,3m-1)
1	5.14	-0.24	3.96	-1.82	1.89	-0.35	6.08	0.39
2	-2.63	-1.54	-4.63	-3.89	-0.35	-0.04	-0.99	-0.48
3	5.75	6.65	7.24	4.71	3.53	4.91	2.98	2.57
4	8.75	2.98	7.02	0.50	7.08	6.68	5.82	5.03
5	3.65	3.90	7.17	6.30	13.88	9.10	11.49	7.07
6	6.60	4.61	12.67	5.42	13.49	8.64	12.36	7.01
7	6.21	9.20	8.17	9.82	10.31	10.97	14.43	10.53
8	5.20	5.46	8.06	7.30	11.32	11.98	15.63	11.54
9	6.09	13.69	11.49	20.27	12.82	18.63	12.50	17.41
10	-1.96	0.68	3.07	4.86	5.90	11.70	10.28	14.21

Table 33 lists the results for forecasts of tercile Yilgarn wheat yields using the monthly diurnal temperature range at Kalgoorlie and Merredin. Higher overall skill was achieved when using the DTR over mean minimum, mean maximum temperatures, SSTs or the SOI, with useful skill levels appearing as early as March/April. The results from Table 33 are shown graphically in Figure 12. Similar skill levels were obtained when forecasting above/below median wheat yields.

Table 33.LEPS skill scores for Yilgarn wheat yields (terciles) using Kalgoorlie or Merredin monthly diurnal temperature range. The predictor month used to forecast the yield is given in brackets. For example, the first row of data is for January (m=1) and predictors using (m, m-2) use January and November (of the previous year). Kal = Kalgoorlie, Mer = Merredin. “-“ indicates no LEPS score available.

Month	Kal (m)	Mer (m)	Kal (m,m-2)	Mer (m,m-2)	Kal (3m)	Mer (3m)	Kal (3m,3m-1)	Mer (3m,3m-1)
1	3.49	-0.91	-	-	2.37	0.86	3.11	1.64
2	-1.77	0.57	-	-	1.76	2.05	0.18	1.24
3	12.71	10.73	12.18	9.10	7.17	5.59	-	-
4	29.45	14.66	28.11	12.57	16.73	10.92	-	-
5	7.42	4.31	16.13	11.46	27.68	18.38	25.70	16.44
6	7.03	3.97	30.13	15.69	27.90	19.79	29.37	19.64
7	12.50	12.82	15.99	14.17	20.61	16.55	29.42	21.63
8	-0.85	-0.99	6.61	3.41	14.79	10.85	27.86	20.00
9	4.46	7.13	14.79	17.09	12.35	11.44	20.04	18.46
10	-2.28	-2.45	-3.30	-3.56	0.68	1.46	12.83	9.39

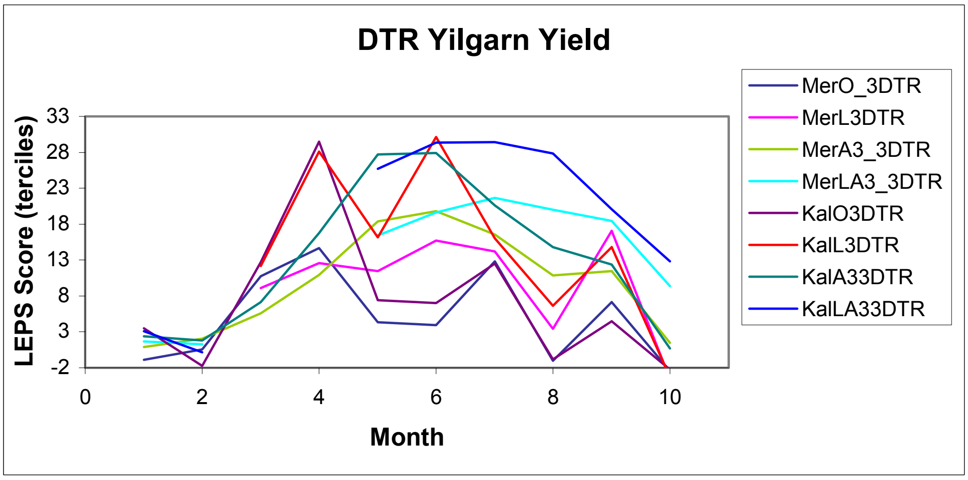

Figure 12. LEPS skill scores for forecasts of median wheat yield at Yilgarn by month using the DTR at Kalgoorlie or Merredin as predictors. The legend is as in Figure 10.

Discussion

Skilful prediction of wheat yield at Yilgarn appears possible using monthly rainfall values from Kalgoorlie or the diurnal temperature range at Merredin or Kalgoorlie, from as early as March. However, caution in interpreting these results is needed as high levels of skill around the time of planting may simply be a reflection of farming practices under prevailing rainfall and temperature regimes.

An illustration of the skill obtainable in this way is shown in Figure 13, where detrended yield is plotted against April Kalgoorlie rainfall. The separation of high yield and low yield years is quite clear.

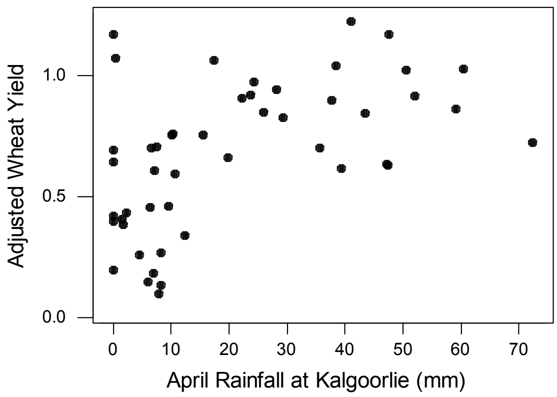

Figure 13: Wheat yield at Yilgarn (detrended) versus April rainfall at Kalgoorlie

Antarctic Circumpolar Wave (ACW)

Description.

The Antarctic Circumpolar Wave (ACW), first documented by White and Peterson (1996) is a large scale anomaly pattern in sea surface temperature (SST), sea level pressure (SLP) and associated wind fields. It is found in the Southern Ocean between approximately 40°S and the Antarctic coast, and consists of a wave number two pattern (i.e. two positive and two negative anomaly regions around a latitude circle). This pattern propagates eastward at about 45° longitude per year, resulting in a four year period at any point. The structure of the ACW is revealed in an EOF analysis of monthly SST anomalies over the Southern Ocean (25S to 65S), in Figure 14. The first two EOFs are in quadrature, ie they have the same basic spatial structure, but displaced by one half a wavelength, so that maxima or minima in one pattern coincide with nodal (zero) lines in the other. The principal components (EOF time series) are uncorrelated at zero lag, but strongly correlated at approximately 12 months lag, implying a 4-year periodicity in the evolution of the pattern.

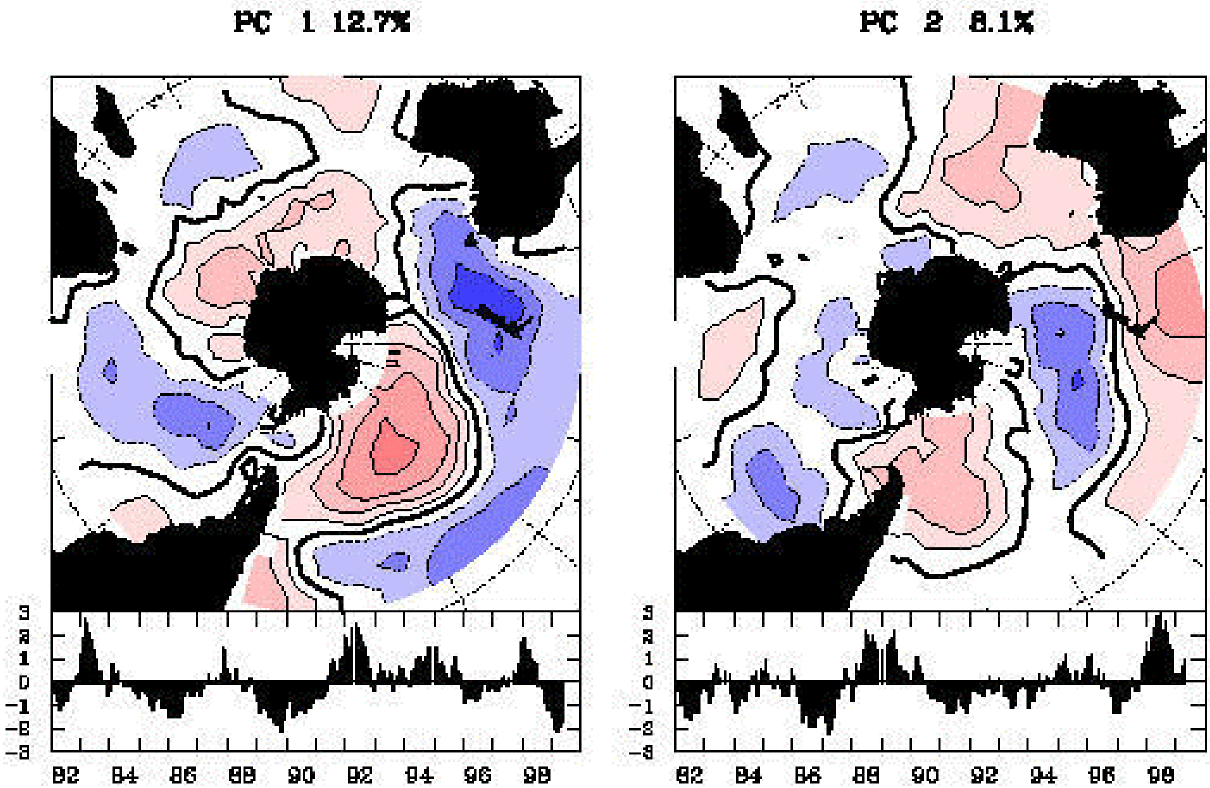

Figure 14. Spatial patterns and time series of first two EOFs of Southern Ocean (25S to 70S) monthly Sea Surface Temperature anomalies for period from January 1982 to April 1999. Contour interval 0.2, with zero contour heavy. Positive loadings shaded red, negative blue.

The propagating character of the ACW can also be seen in a Hovmoller (time - longitude) plot of SST and SLP anomalies along a latitude band (eg 50-60S, figure 15). Alternatively, the evolution of the EOF patterns can be tracked on a phase plot of

the two principal components (figure 16). As the wave propagates eastward, the observed SST anomaly pattern should project strongly onto a sequence
... +PC1 → +PC2 → -PC1 → -PC2 → +PC1…
Predictability of the ACW is largely based on the persistence of this approximately 4-year cycle.

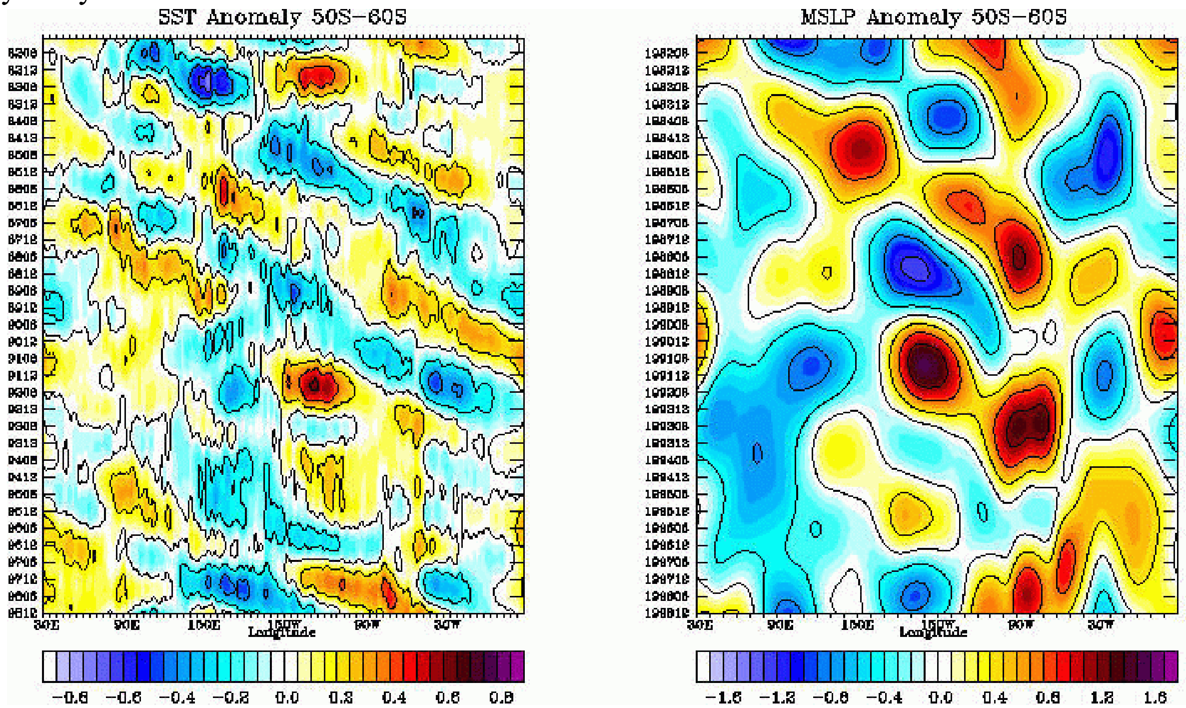

Figure 15. Hovmoller (time - longitude) plots of (a) SST anomalies and (b) MSLP anomalies for period Jan 1982 to Dec 1998, averaged over a 10 degree latitude band form 50S to 60S. Data is 2-7 year band pass filtered and has zonal mean removed.

Relations to the El Niño - Southern Oscillation and the Indian Ocean Dipole

Peterson and White (1998) suggest that ACW has a source region in the subtropical southwest Pacific, which in turn is driven by equatorial ENSO related anomalies. SST and SLP anomalies propagate from this region into the Southern Ocean. The extent of the ENSO / ACW connection is simply shown by the lagged cross-correlation between the SOI and the principal component time series (Figure 17) The two PCs are themselves uncorrelated at zero lag (as required by the EOF analysis), but are significantly correlated (-0.65) with PC1 lagging PC2 by approximately 12 months. The reverse correlation (PC1 leading PC2) is not as strong (+0.30), suggesting that the evolution of some parts of the nominal four year cycle are more reliable than others. This is also evident in the PC1 - PC2 phase plot (Figure 16) which suggests that the transition from +PC1 to +PC2 is not as robust as the rest of the cycle, which then “begins” with +PC2. This view is consistent with the hypothesis of Peterson and White (1998), since +PC2 has significant warm anomalies in the Tasman Sea region. These appear to propagate to the southeast, surrounding New Zealand in -PC1 and then to the southeast of New Zealand in -PC2. Both PCs have significant lagged correlations with the SOI, also only in one direction for each PC. PC1 lags the SOI by 3-6 months, while PC2 leads SOI by 6 months. The second EOF pattern has positive loadings in the Indian Ocean southwest of Western Australia, in a similar region to the maximum loadings on SST2 defined by Drosdowsky and Chambers (1998). The times series of these components are also significantly positively correlated (+0.58) at a lag of two months. This suggests that subtropical (20S to 35S) Indian Ocean SST anomalies may also be linked to the ACW.

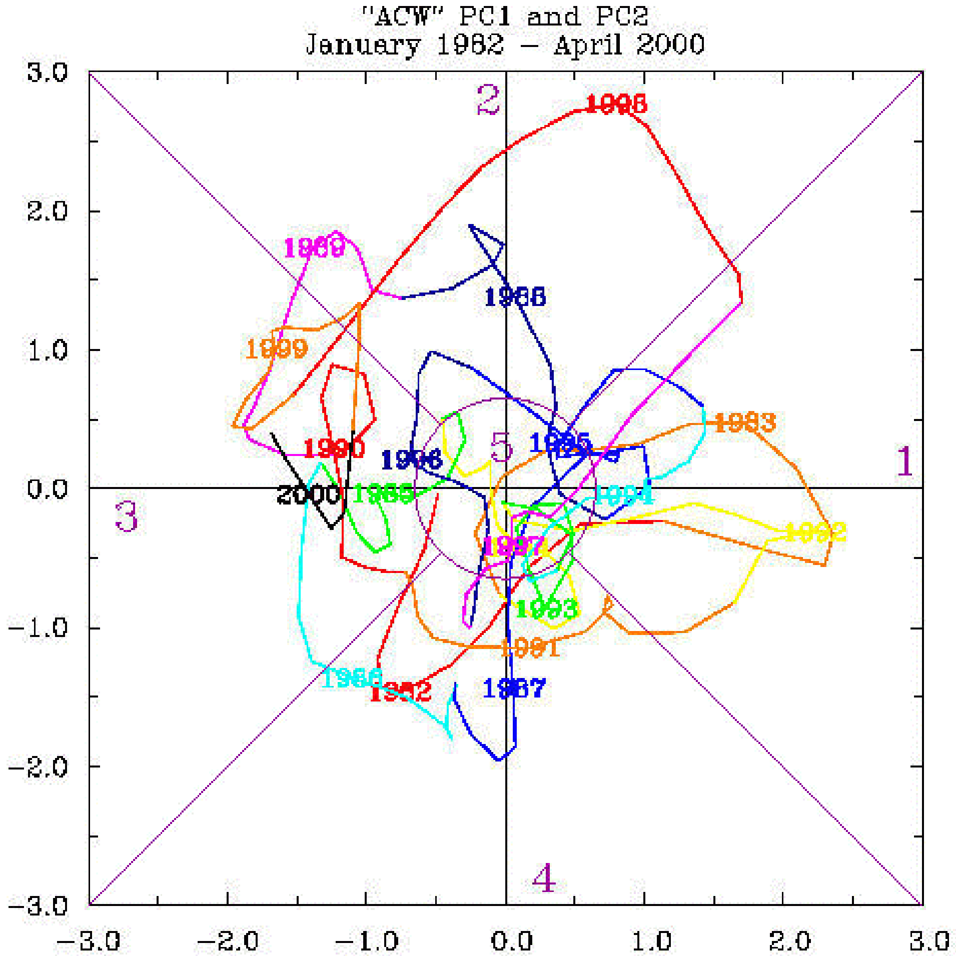

Figure 16. Phase plot of EOF amplitudes PC1 and PC2 for period Jan 1982 to May 2000. Each year is plotted at mid-year (June) point, and colour of trajectory changes each year. Light purple boundaries and numbers 1-5 refer to categories or phases used in Figure 5. Both time series are lightly smoothed with a 1-2-1 filter before plotting.

Effect of the ACW on Australian rainfall.

The ACW has persistent, large scale SST anomalies in the vicinity of Australia, and could therefore be expected to show some relationships with Australian rainfall. To examine this in a fairly simple manner, we adopt a compositing type approach. Each month is characterised as being in one of five phases, depending on which of the two EOF patterns is dominant. The boundaries defining each phase are shown in Figure 16. For each phase we then examine the rainfall distribution in the following season, presented in Figure 18 as the proportion of seasons in which the seasonal rainfall exceeds the median. The strongest signal appears with Phases 2 and 4, i.e., opposite signs in PC2. The positive phase of PC2 is associated with mainly wetter conditions over most of Australia, with drier conditions over the north and east in the negative phase. This is consistent with the relationship between PC2 and the SOI, i.e., PC2 and the SOI are significantly positively related (at six months lag) so that positive PC2 is also associated with positive SOI. PC2 is also related to Indian Ocean SST anomalies, with positive PC2 implying positive SST anomalies in the Indian Ocean west of Australia. These in turn are associated with a dipole pattern in Australian rainfall, with wetter conditions over northern and eastern Australia, and drier conditions along the south coast.

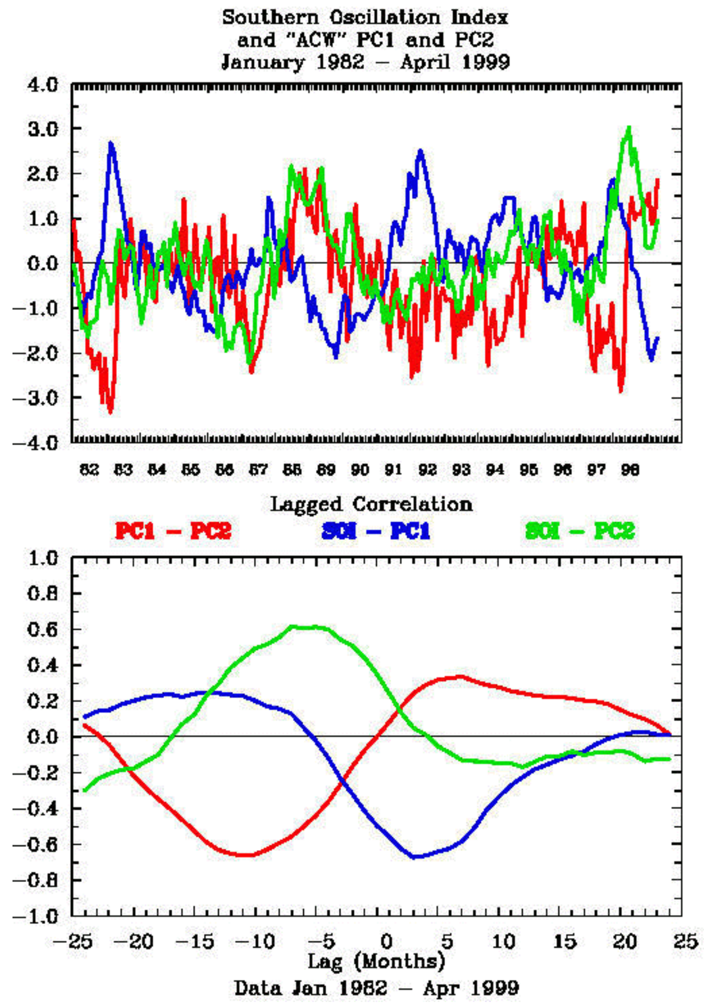

Figure 17(a) Times series of raw monthly values of PC1 (blue), PC2 (green) and the SOI (red) for period January 1982 to April 1999. (b) Lagged correlations between PC1 and PC2 (red), the SOI and PC1 (blue) and the SOI and PC2 (green) based on data in (a).

Summary

The independent skill of the ACW in forecasting Australian seasonal rainfall is therefore is difficult to quantify due to:

(i) The short period of reliable data - i.e., less than twenty years to describe a phenomenon with a nominal 4-year cycle.

(ii) The statistical, if not physical, connections with the El Niño - Southern Oscillation and the Indian Ocean SST anomalies which also have strong known associations with Australian rainfall.

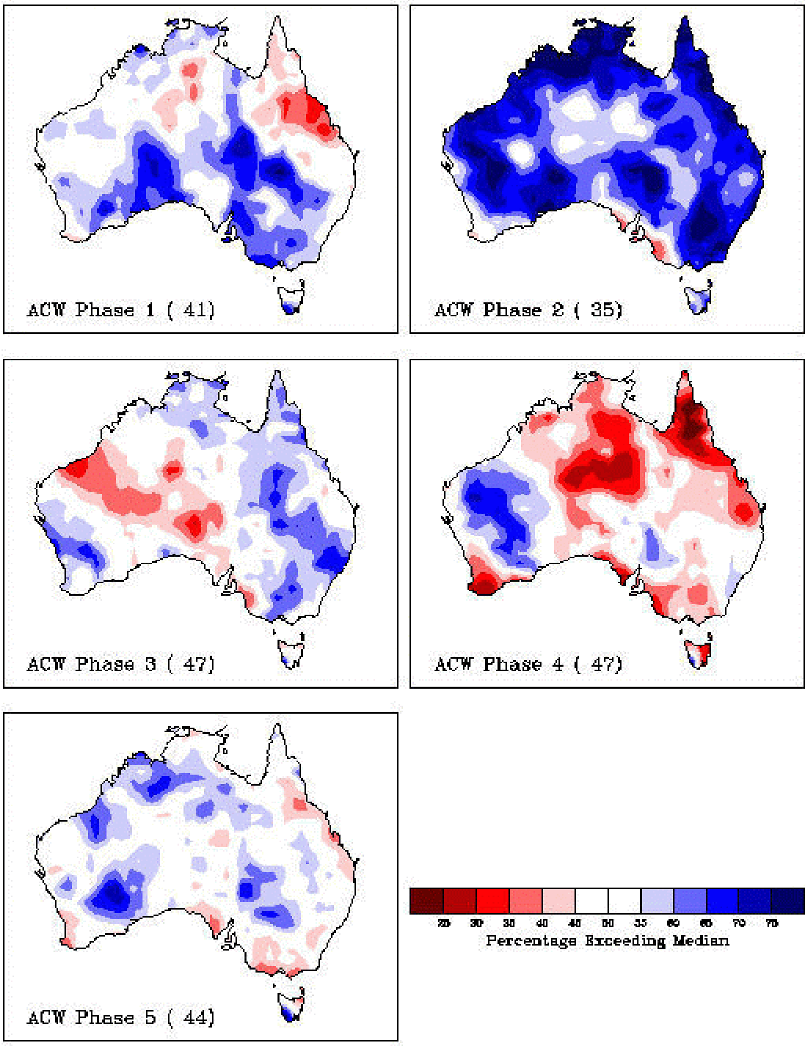

Figure 18. Percentage of seasons exceeding median rainfall following, one month later, months with ACW characterised by the five phases shown in Figure 16 (i.e., for January ACW phase, rainfall is in following March - May, etc).

Equatorial Indian Ocean SST Dipole

Saji et al (1999) and Webster et al (1999) independently proposed that an internal mode of variability in the equatorial Indian Ocean led to a dipole structure in SSTs which could affect the climate of the surrounding region. This dipole mode, it was suggested, was independent of the El Niño - Southern Oscillation. The strength of the dipole, measured by the equatorial SST gradient across the Indian Ocean, was only weakly, and non-significantly, correlated with the El Niño, according to both sets of authors. If this was so, then the strength of the dipole may have some influence on rainfall in Western Australia, separate to the influence of the El Niño - Southern Oscillation. It was thought worthwhile, therefore, to more carefully examine the independence, or otherwise, of the dipole mode. It should be noted that this dipole is somewhat distinct from the dipole-like correlation structure described by Nicholls (1989), that exhibited more latitudinal structure.

In fact the apparent "independence" of the equatorial dipole from the El Niño is an artifact of calculating correlations using all months on record, rather than first stratifying the data by season. For instance, if only the average September-November data are used then the correlation between NINO3 SST and the Indian Ocean dipole index defined by Webster et al. (1999) is 0.56 (data from 1958-97, p<.001). Time series of the two indices are shown in Figure 19. Apart from an occasional year (e.g., 1961) the strong relationship between the two is clear. Thus the equatorial Indian Ocean dipole is NOT independent of the El Niño - Southern Oscillation.

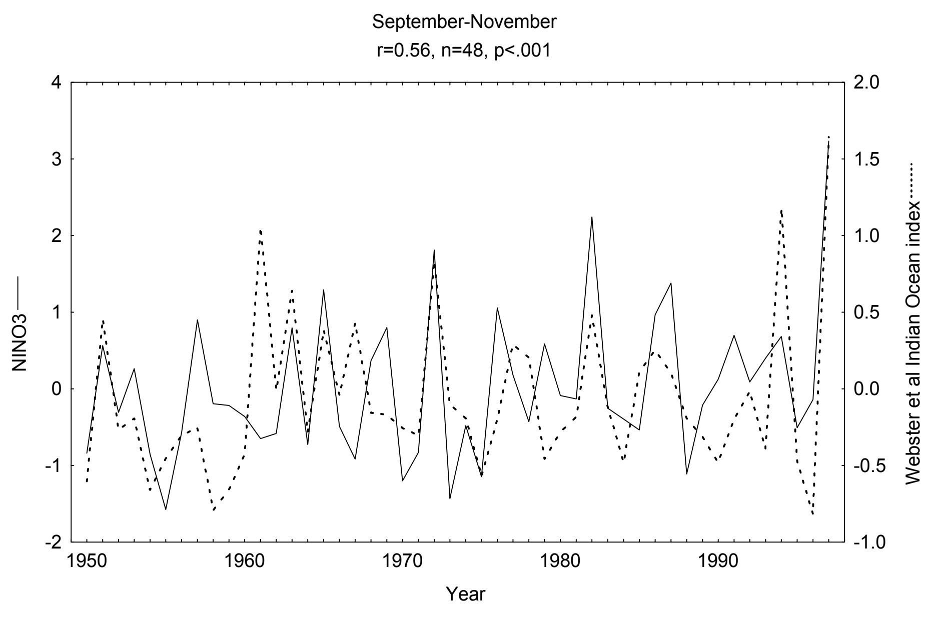

Figure 19. Time series of NINO3 SST anomalies and the Webster et al. (1999) index of the strength of the equatorial Indian Ocean SST dipole.

Closer examination reveals that the dipole of Saji et al. (1999) and Webster et al. (1999) is not even a dipole. If it was then there should be a consistent negative correlation between the western and eastern boxes that constitute the index of the dipole strength. The correlation between the western and eastern boxes, again for September-November only, is actually only -.13 (n=40, non-significant). The time-series of the two boxes are shown in Figure 20. Interestingly, there are periods when there does appear to be some evidence of "dipole-like" behaviour (eg., the last few years of the time series). There are other periods however, when there is no evidence of such behaviour.

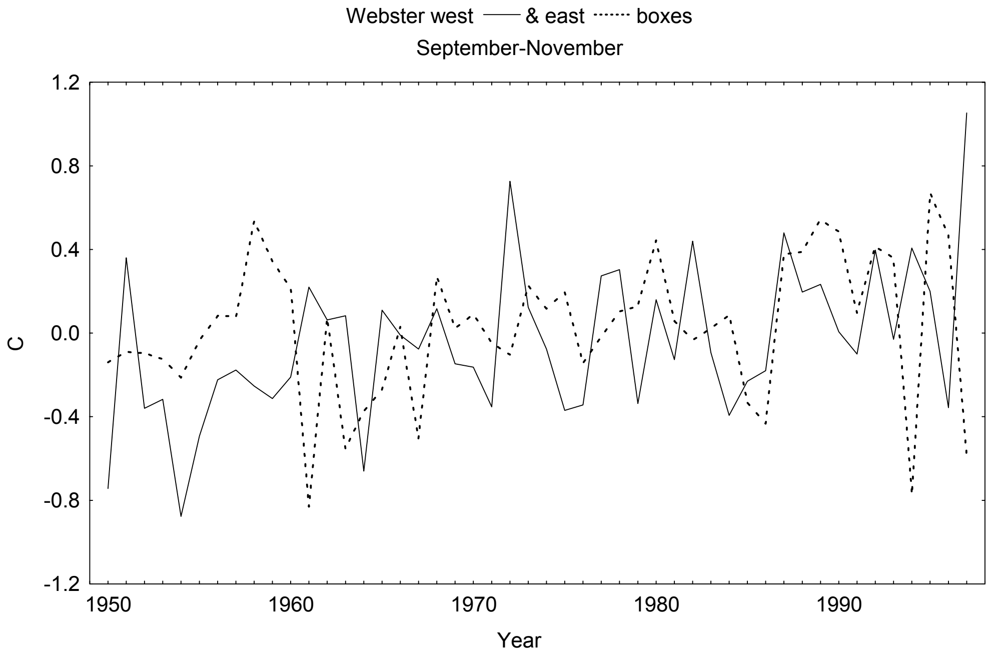

Figure 20. Time series of the eastern and western boxes of the Webster equatorial Indian Ocean SST dipole index.

Note that in Figure 20, there is clear evidence of an increase in SST over time, in both boxes. This warming would tend to offset any underlying negative correlation between the two boxes. That is, the coherent warming would confound the identification of a dipole-like structure. In order to determine the strength of this dipole-like behaviour we need to de-trend the SSTs in the two boxes. If this is done by linear regression against time, and the residuals from this de-trending are calculated, then the correlation between the two boxes is -.21. The larger magnitude of this correlation confirms that the warming trend is offsetting the tendency for a dipole-like structure.

So there is a weak dipole-like structure but, as we saw earlier, the strength of this dipole is closely related to the El Niño - Southern Oscillation. Is there any dipole-like behaviour other from that imparted by the El Niño - Southern Oscillation? To answer this we calculate the linear regressions of the SSTs in the two Indian Ocean boxes against NINO3 SSTs, then correlate the residuals. Note that this has been done after detrending of all SSTs to remove the coherent warming. The final residual SSTs in the two Indian Ocean boxes now have a correlation of –0.04 (n=40, not significant). That is, once the effect of coherent warming and the El Niño - Southern Oscillation are removed, there is essentially no dipole-like behaviour in the Indian Ocean. What dipole-like behaviour is found in the equatorial Indian Ocean simply reflects the differential effect of the El Niño - Southern Oscillation on the two edges of the ocean.

This reflects the overall situation. However, if the time series of the residual SSTs in the two Indian Ocean boxes are examined (Figure 21), a somewhat different pattern emerges. Now we find that there are periods when there does appear to be a strong dipole-like behaviour (1990 to date; 1958-1965), with another period (1970-1990) when the variations of the two boxes are in phase. That is, the lack of correlation between the two edges of the equatorial Indian Ocean does not reflect random variations but two possibilities of either the entire ocean acting as a dipole or both sides varying coherently.

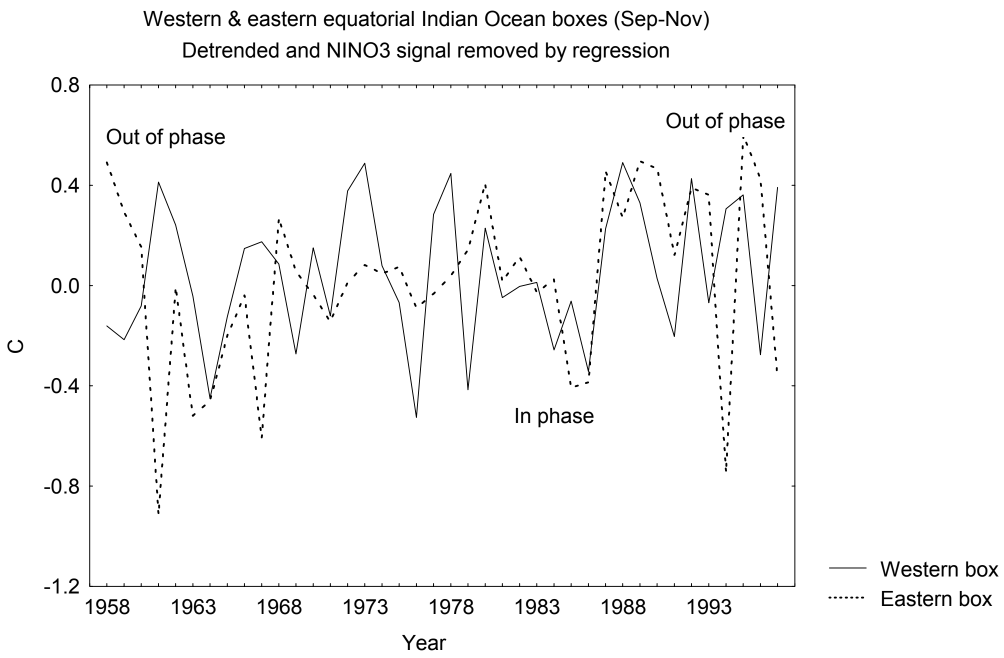

Figure 21. Time series of the western and eastern boxes comprising the Webster et al. (1999) dipole index, after detrending and removing the relationship with NINO3 SSTs.

Summary

There is no evidence of a consistent dipole-like behaviour in the equatorial Indian Ocean, apart from that imparted by the El Niño - Southern Oscillation. There are, however, periods when a dipole-like structure and behaviour appears. These are offset by other extended periods when both sides of the equatorial Indian Ocean vary in phase. This intriguing behaviour should be further investigated, to determine whether either form of Indian Ocean behaviour impacts on the countries surrounding the ocean.

Causes of decadal decline in rainfall in SWWA

There were three (initially two) aspects of this part of the study:

- *Examine long integrations of the BMRC climate model, forced with observed SSTs, to determine whether these reproduce the observed decline in rainfall*. The results from this were expected to provide guidance to the likely causes of the decline in rainfall. This part of the study has been delayed because of delays in obtaining the SSTs, and the extra work required for the first part of the Second Research Phase, and because of the addition of the third aspect of this part of the study (see below). However, some of the results obtained under the third aspect of this part of the study (see below) shed light on this question.
- *Use path analysis to examine relationships between possible predictor variables and rainfall.* Path analysis studies were reported in the Phase 1 report.
- *Investigate whether long-term variations in SWWA rainfall are related to distant factors (e.g., rainfall trends in other parts of the globe).* This aspect was added in May 2000, at the request of the IOCI Panel. The analysis has been done using the Climate Explorer web site of KNMI, using standard global data sets.

The first step was to determine other areas where precipitation had exhibited a similar (downward) trend to that of SWWA. Precipitation was correlated with year to determine trends; the result is shown in Figure 22. The area of SWWA exhibiting a decline in rainfall over the period 1958-1998 is quite small in this analysis (because the data set is on a relatively crude grid). The area with the most obvious decline is the Sahel. Areas with increases are found in eastern Europe and North America.

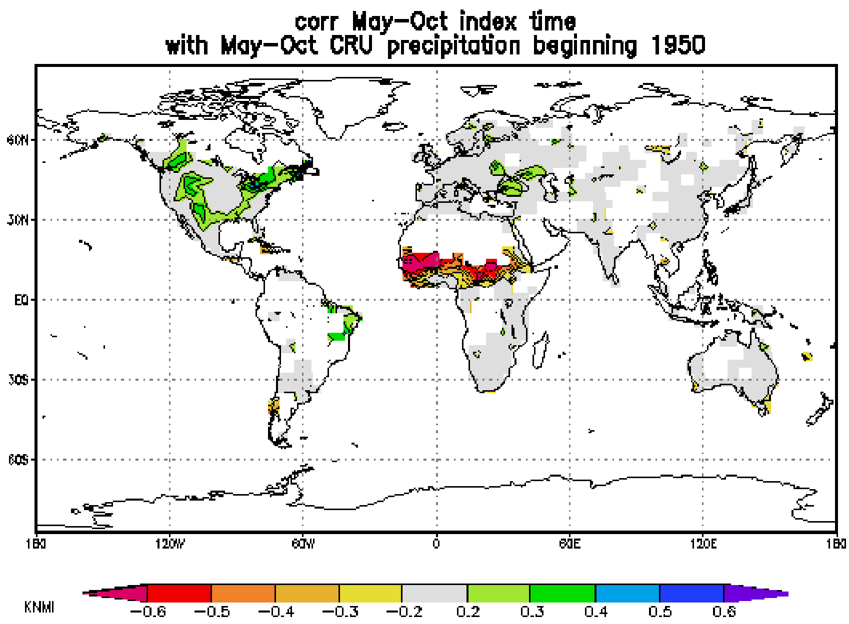

Figure 22. Correlation of year with precipitation from the CRU data set (?).

How are the trends in SWWA and the Sahel and elsewhere related? Figure 23 shows the correlation between observed rainfall at Manjimup and observed rainfall elsewhere in the world. There are strong positive relationships with rainfall across southern Australia, and in the Sahel. There are negative correlations with North America rainfall.

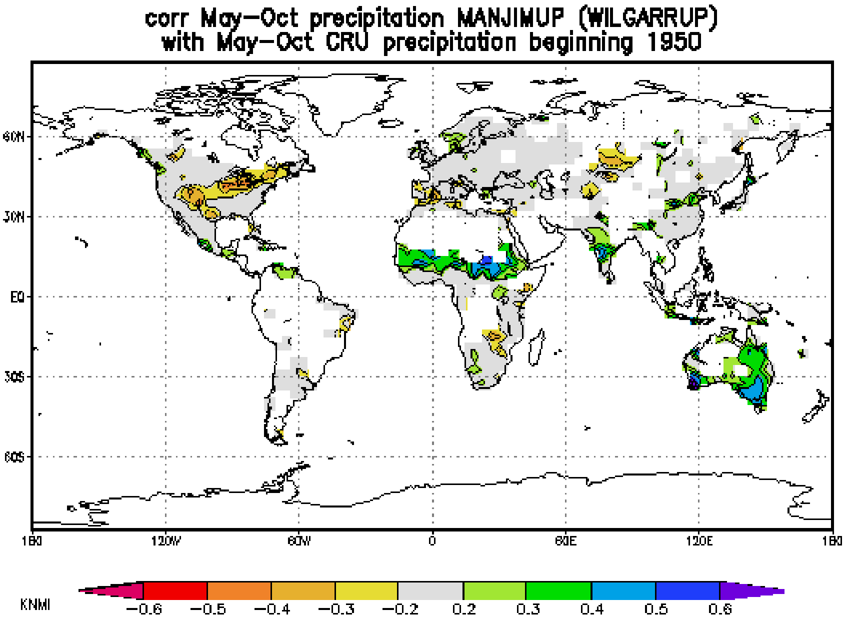

Figure 23. Correlation of Manjimup May-October rainfall with May-October precipitation elsewhere.

However, these correlations may simply reflect similar downward trends, rather than a more fundamental relationship which would also lead to strong correlations between interannual variations. This is clear from Figure 24 which shows the correlations of detrended rainfall across the globe, with detrended rainfall at Manjimup. The correlations with Sahel rainfall are weaker than with the original rainfall data, indicating that the correlation largely reflects the downward trends. Note that the detrended rainfalls in India are closely positively related to southern Australian rainfall. This reflects part of the global El Niño - Southern Oscillation pattern.

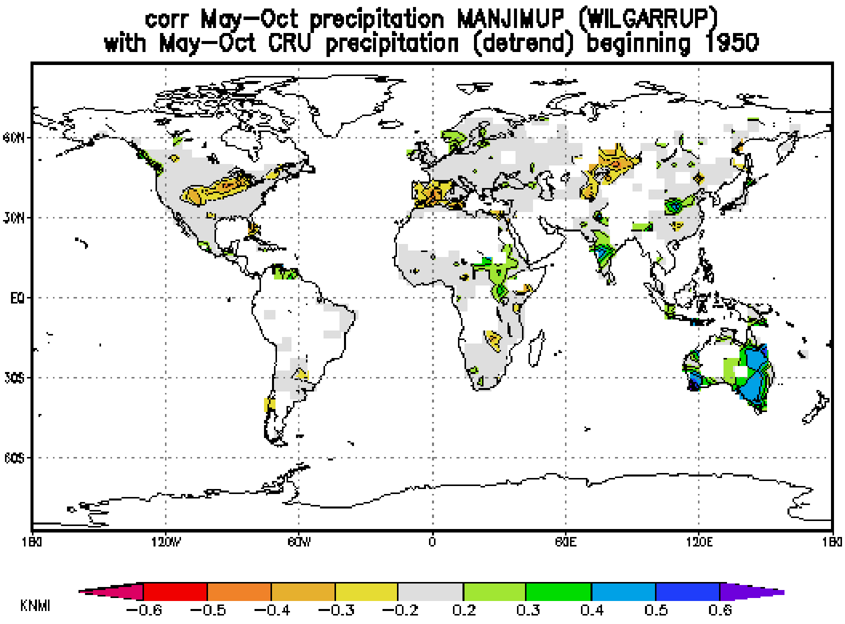

Figure 24. Correlation of Manjimup May-October rainfall with May-October precipitation elsewhere (all rainfalls detrended before correlations were calculated).

How are the precipitation trends shown in Figure 22 related to trends in temperatures, especially SSTs? Figure 25 shows the trend in sea surface and near-surface temperatures over land. Large increases are obvious in the Indian Ocean.

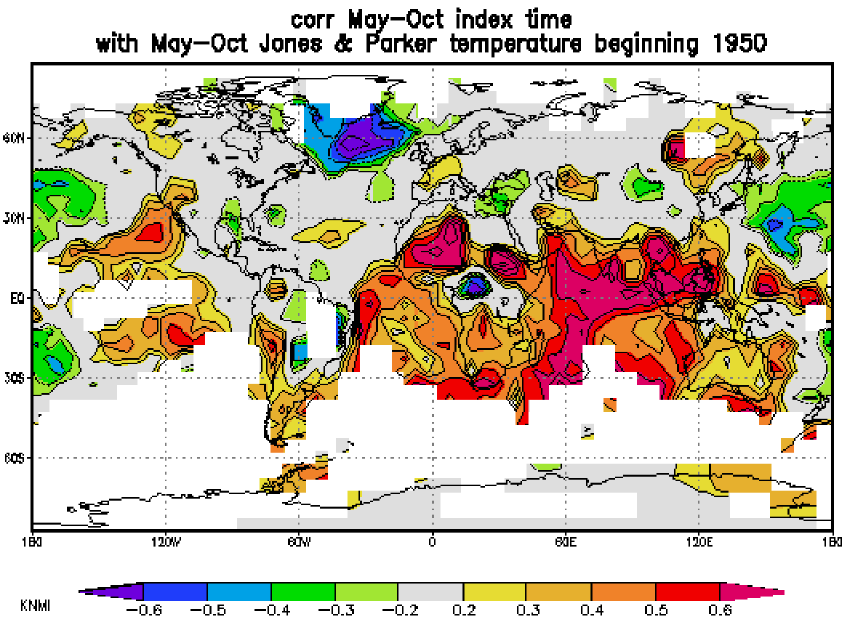

Figure 25. Correlation of near-surface temperature with time.

The trend in precipitation from the NCEP reanalyses is shown in Figure 26. These trends should be related to the trends in surface temperature, shown in Figure 25, if the SST trends are causing the precipitation trends. In fact the figure reproduces the strong downward trend in precipitation over the Sahel. However, the figure shows increasing rainfall across Australia. This suggests that the decline in rainfall over SWWA is not related to, or forced by, trends in SSTs in the Indian Ocean (or that the model is unable to correctly reproduce interactions with SSTs leading to changes in SWWA rainfall).

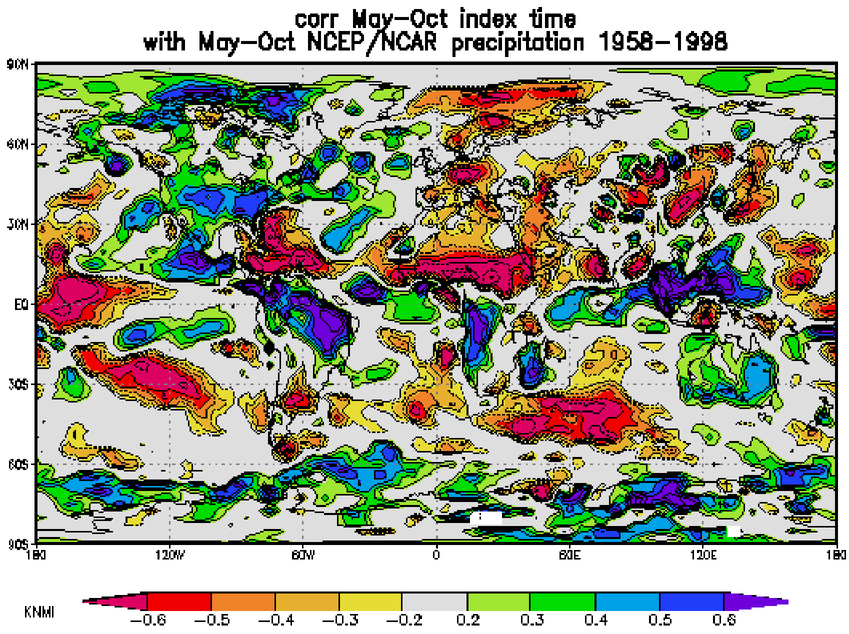

Figure 26. Correlation of NCEP "precipitation" with year.

Figure 27 shows the correlation with Manjimup precipitation and near-surface temperatures across the globe. Strong correlations are evident with Indian Ocean SSTs.

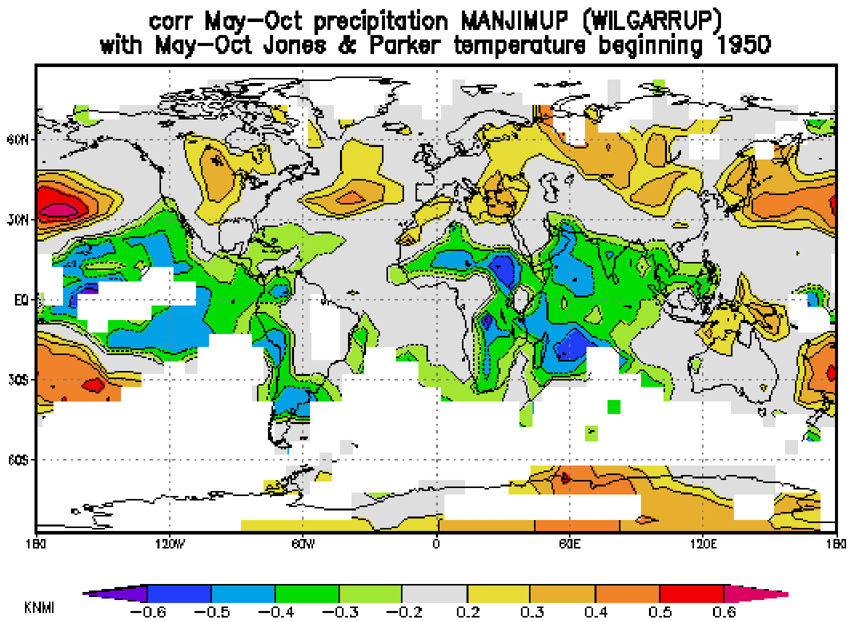

Figure 27. Correlation between May-October Manjimup rainfall and near-surface temperatures.

The correlations are substantially weaker if the data are detrended first (Figure 28). This tends to confirm the point made above, that the trend in precipitation at Manjimup (and elsewhere in the SWWA) is NOT directly related to the variations in Indian Ocean SSTs. Note that the pattern of correlations with SSTs in the Pacific Ocean is very much indicative of a relationship with the El Niño.

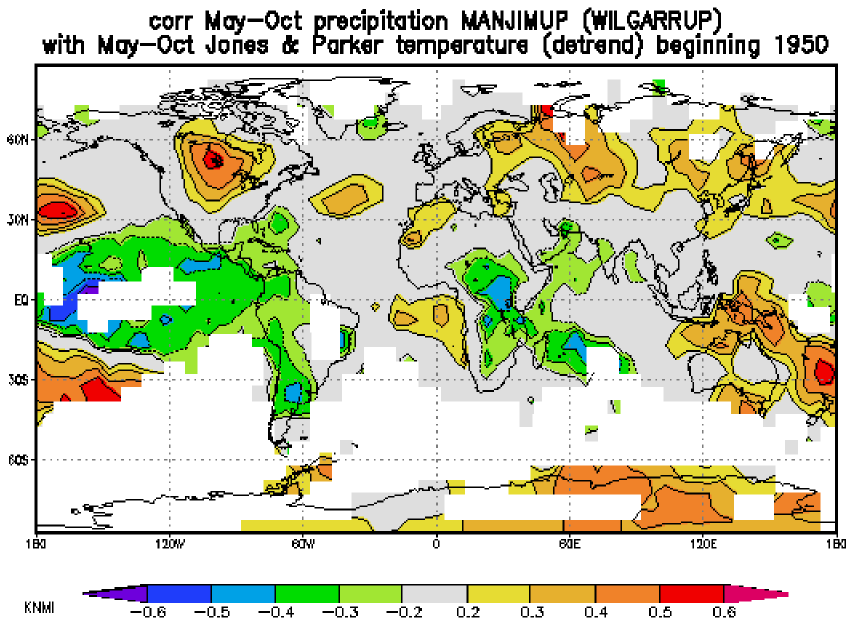

Figure 28. Correlation between May-October Manjimup rainfall and near-surface temperatures. Data detrended before calculation of correlations.

The correlation of Manjimup with (detrended) NCEP surface pressures (Figure 29) shows that an increase in pressure over and surrounding Australia, and stretching to the west, accompanies low rainfall in SWWA. Low pressures are usually found in the eastern Pacific. This pattern is somewhat similar to the pattern of pressure anomalies associated with an El Niño.

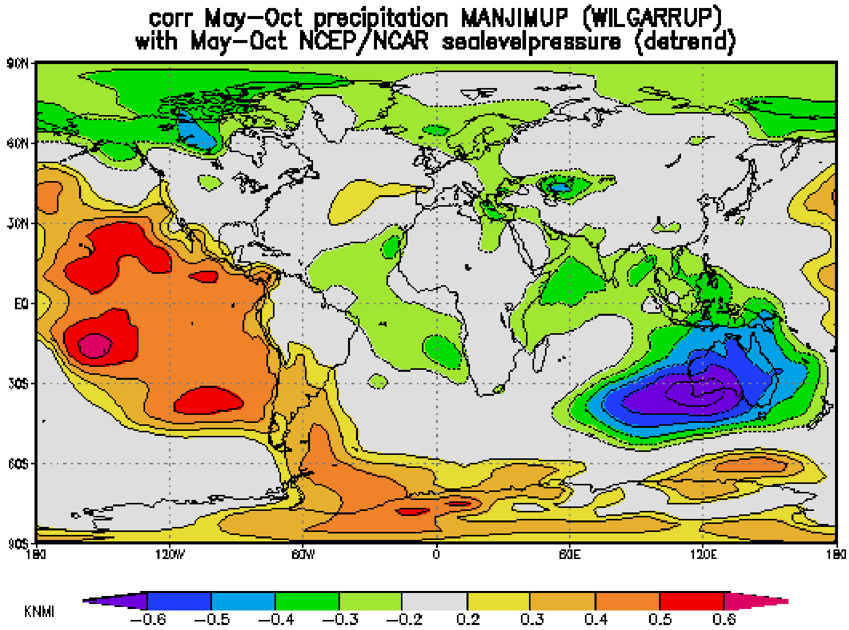

Figure 29. Correlation between May-October Manjimup rainfall and sea level pressure from NCEP reanalyses. Data detrended before calculation of correlations.

Figure 30 shows the trend in pressure from the NCEP reanalyses. Although the trends over the oceans, especially the southern oceans, are very suspect, trends over the continents should reflect reality. Over western Australia there has been a trend towards higher pressures. This would not be surprising, given the decline in rainfall in SWWA. However, why the NCEP reanalyses, despite this increase in pressure, also produces an increase in rainfall across the continent is not obvious.

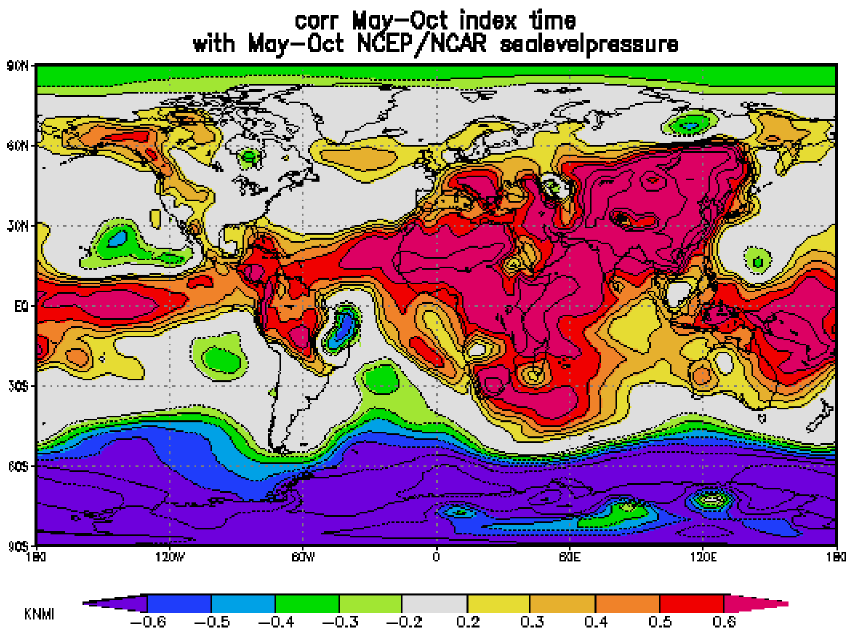

Figure 30. Correlation of year with sea level pressure. Note that the values over the southern oceans reflect changes in observing systems, rather than real trends.

Summary

This study does tend to confirm earlier work (reported in the BMRC report on Phase 1 work) suggesting that the decline in SWWA rainfall is not simply attributable to change sin Indian Ocean SSTs. However, there are problems with the use of NCEP reanalysis data to investigate this question, so the answer, at this stage, is not conclusive. If, however, further work does conclude that the decline is related to the changes in SSTs, we anticipate that the mechanism by which this is affected must be subtle (otherwise the analyses described here and in the BMRC report on Phase 1 work should have provided some support for this hypothesis).

CONCLUSIONS

This report describes the results of comprehensive BMRC studies of the predictability of interannual variations of SWWA Australia climate, and some study of the possible cause of the multi-decadal decline in SWWA winter rainfall. Not all of the work planned for the Second Research Phase has been carried out. In particular, studies using the BMRC climate model have not been completed (partly due to unexpected delays in obtaining new global SST fields). On the other hand extra work, in addition to that agreed to in the Second Research Phase plan, has been undertaken, at the request of Panel members. Specifically, spring predictability and wheat yield predictability has been investigated, along with the possible use of the equatorial Indian Ocean "dipole" in prediction of SWWA climate. As well, the possible use of SST gradients in prediction has been studied.

The major findings of the Second Research Phase BMRC work, are:
We found:

- Some skill in predicting
  - Spring and summer rainfall
  - Spring and summer temperature
  - Summer extreme temperatures
- More skill with SST1 or SST1 & 2 as predictors, than with SOI
- Little skill in predicting winter rainfall
- Considerable skill in predicting wheat yield (from observed climate)
- Little skill predicting for the SWWA from SST gradients in the southeast Indian Ocean
- "Differencing" of data (to avoid "breaks" in relationships) did not lead to improved forecasts
- The ACW seems related to Australian rainfall, but extra predictability provided by the ACW is difficult to quantify
- The equatorial Indian Ocean "dipole" is not really a dipole. But there is evidence that some behaviour in the Indian Ocean is independent of the El Niño - Southern Oscillation (and may therefore add to SWWA predictability studied thus far)
- Further evidence that the decline in SWWA winter rainfall is not simply due to changes in Indian Ocean SSTs.

ABBREVIATIONS & GLOSSARY

ACW: Antarctic Circumpolar Wave
DTR: Diurnal temperature range
EOF: Empirical orthogonal function
LEPS: Linear error in probability space
Loadings: Spatial pattern of EOF
MSLP: Mean sea level pressure
Scores: Time series of EOF values
SLP: Sea level pressure
SOI: Southern Oscillation Index
SST: Sea surface temperature
SST1: First EOF of Indian & Pacific Ocean SST
SST2: Second EOF of Indian & Pacific Ocean SST
SWWA: Southwestern Western Australia

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