SEACI Project 3.1.3 Milestone Report

Assessment of simulation by POAMA of modes of climate variability that drive rainfall in SE Australia

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1. Introduction

The Bureau of Meteorology routinely makes dynamical seasonal predictions out to 9 month lead time with the POAMA coupled ocean-atmosphere forecast system. The main focus for POAMA-1 is the prediction of sea surface temperature (SST) anomalies associated with El Niño / La Niña, for which POAMA's predictions are internationally competitive. El Niño/Southern Oscillation (ENSO) is the dominant driver of Australian climate variability, thus POAMA's forecasts have great value for anticipating the behavior of El Niño.

Although the primary focus to date has been on prediction of El Niño, POAMA does provide predictions of regional climate. There has been little use of the regional climate forecasts from POAMA1 due to a number of model limitations. For instance, the atmospheric model in POAMA is run at relatively low horizontal resolution such that regional rainfall variability around Australia is not well resolved. And, the mean climate from the POAMA model drifts, thus hindering the use of direct prediction of regional climate at longer lead times. Nonetheless, an assessment of POAMA's ability to simulate the major modes of climate variability that are relevant to Australian climate is in order. This assessment is required to provide a benchmark for future improvements of the forecast systems, such as that anticipated by development of the ACCESS system (e.g., improved spatial resolution, improved physical parameterizations, and reduced model drift). This assessment is also required because the utility of the forecasts from the current version of POAMA is unknown. There is also scope for bridging and downscaling of the forecasts, which is founded on the notion that important climate drivers (primarily ENSO teleconnections) are predicted. This report summarizes an initial assessment of the prediction/simulation by POAMA 1.5b of the major drivers of Australian rainfall variability. The focus is not only on ENSO but also on other tropical sea surface temperature variations such as those in the equatorial eastern Indian Ocean that are important for SE Australian rainfall. We will also assess the impact of model drift on these relationships, which should aide future development of the POAMA system.

2. Hindcasts and mean state bias

The analysis here is based on a 3 member ensemble of 9-month forecasts for the period 1982-2006. Forecasts are initialized from observed atmospheric and ocean initial states. The atmospheric initial state, together with the land surface condition, is produced by the ALI system. The ocean initial condition is provided by the ocean initialization system that piggybacks on the POAMA system. Forecasts are initialized on the first of each month. Three forecasts are made each month from slightly different atmospheric initial conditions but with identical oceanic initial conditions.

Forecast anomalies are formed relative to the forecast model mean state, which is a function of start month and lead-time. In this fashion, the mean model bias is removed. A critical issue, however, is whether the bias then affects the variability (which is what we are trying to predict). The simulated mean rainfall for the DJF and JJA seasons, as a function of forecast lead-time, is displayed in Figures 1 and 2. The overall pattern of predicted rainfall is realistic, but much too weak. However, there is very little evidence of model drift: the mean rainfall is equally poor (or good, depending on your perspective) for all lead times. But, as will be shown below, model drift affects the structure of the ENSO mode and its teleconnection to Australia, hence simply removing the bias after the fact is no substitute for reduction of the bias. Reduction of the mean climate bias is a primary focus of the ongoing improvement of the POAMA system.

3. Simulation of major modes of SST variability

We first assess POAMA's ability to simulate the major modes of SST variability that are relevant to Australian climate variability. Foremost is ENSO. Recently, Wang and Hendon (2007) emphasized that the eastern Australia rainfall is equally sensitive to the "inter-El Niño" variations of SST, which are the east-west shifts of SST anomalies in the central Pacific between different El Niño/La Niña events. These shifts are well captured by the second leading EOF of SST variability. The structures of the first 2 EOFs of SST from the hindcasts that verify in DJF are displayed in Fig. 3. The results for DJF are typical of the other seasons. At lead time 0, the spatial pattern of the EOFs is nearly identical to the observed patterns (reflected by the strong pattern correlations with observed in Table 1). At longer lead-times, some important drift in the leading EOF (the "ENSO" mode) is seen. The major drift is the extension of the warm anomaly associated with the El Niño all the way across the Pacific into Indonesia. This stems from the drift in the mean SST (not shown), whereby the cold tongue of SST erroneoulsy extends across the Pacific at longer lead-time. Nonetheless, both EOF 1 and 2 retain some realism out to at least lead time 6 (Table 1).

The skill for prediction of the temporal variation of these leading modes of SST is assessed by the correlation of the predicted and observed principal components (Table 1). In general, EOF 1 (the ENSO mode) is predictable out to at least 6 months, while EOF 2 is predictable for about 4-5 months, as indicated by a correlation greater than 0.5. An alternate way to assess the skill of prediction of the leading modes of SST variability is to assess skill of the projections of POAMA SST onto the observed EOFs of SST (Table 2). It is now seen that POAMA can skilfully predict the observed behavior of EOF 1 and 2 out to at least 6 months for all seasons. EOF 3 is generally predictable for about 4 months. The overall conclusion, then, is that POAMA can skilfully predict the patterns of tropical SST variability that are important for Australian climate with lead time out to about 6 months.

4. Simulation of the major drivers of rainfall variability

We now assess POAMA's ability to simulate the teleconnection between the leading modes of tropical SST variability and Australian rainfall. As discussed above, Australian rainfall is sensitive not only to the dominant ENSO mode of SST variability, but also to the east-west variations of tropical SST about El Niño. This is demonstrated in Figs. 4 and 5 (center panels), which show the correlation of observed rainfall with the observed EOFs 1 and 2 of tropical SST for the winter (JJA) season. Correlations are generally negative with both EOFs across eastern Australia (warm SST in the central Pacific is associated with reduced rainfall in eastern Australia). But, rainfall in parts of central eastern Australia is more sensitive to EOF2 than EOF1. In spring (Fig. 6 and 7), a similar relationship is seen, but now EOF1 is more dominant than EOF 2 in the east.

POAMA's ability to simulate these relationships is shown in the panels around the perimeter of these figures, as a function of forecast leadtime. The impact of model drift on the relationship with EOF 1 is stunning. For instance in JJA (Fig. 4), POAMA does a modestly good job representing the negative relationship on the east coast at short lead time (ie. reduced rainfall during El Niño). But, at longer lead-time, POAMA simulates exactly the wrong response (enhanced rainfall in the SE during El Niño). Similarly in SON (Fig. 6) POAMA under represents the negative relationship at short lead time, and then over does the negative relationship at long lead time. Similarly in DJF (Fig. 8), POAMA does a good job at short lead time, and then over represents the reduction of rainfall during ENSO at long lead time. Drift seems to be less of an issue for EOF2. Overall, then, the current version of POAMA appears to do a credible job of simulating the rainfall teleconnections associated with the main modes of SST variability at short lead time, but model drift appears to hinder this simulation at longer lead times.

The behavior for simulation of rainfall in the SEACI region (38.5°-33.5°S, 137.5°-152.5°E) is shown in Figs. 9-11. The correlation between the predicted rainfall in the SEACI region and predicted SST is shown as a function of lead time. For JJA (Fig. 9), POAMA exhibits realistic sensitivity at short lead time (wet when central Pacific is cold and the seas around Australia are warm) but at longer lead time the simulated sensitivity changes sign. For SON (Fig. 10) the SST pattern is realistic at all lead times (wet during La Niña), but at long lead time, the relationship is much too strong. For summer (DJF Fig. 11), POAMA also couples SEACI rainfall too strongly to ENSO. These relationships are summarized in Tables 3 and 4, which show the correlations between predicted Australian-mean rainfall and predicted SST EOFs. The observed relationships are also provided for reference.

5. Conclusions and recommendations

POAMA has skill in predicting tropical SST variations that are important for Australian climate. This includes not only skill in predicting ENSO, but also extends to the important east-west variation of equatorial Pacific SST of individual ENSO events. Eastern Australian rainfall, especially in winter and spring, is sensitive to these east-west variations of SST, hence, POAMA appears to have important predictive capability beyond simply that of the occurrence of El Niño.

POAMA also realistically simulates rainfall teleconnections to Australia driven by ENSO and the inter-ENSO variations of SST. However model drift appears to degrade the realism of these teleconnections at longer lead times. There also appears to be an issue with spin up-, whereby the teleconnection is initially too weak, but then strengthens to realistic magnitudes 1-3 months into the forecast. These results imply that the model drift needs to be remedied and that initialization needs to be scrutinized. One way to alleviate model drift is to “flux correct” in order to maintain a realistic base state. Flux correction should be considered for future versions of POAMA. Improvements to the ocean initialization system are underway, which might remedy some if the apparent initialization shock (spin up) that has been diagnosed here. The impact of the new ocean initialization will be assessed in the coming year as the system becomes available. However, the best approach in the future will be to develop a truly coupled initialization system, whereby the ocean, land surface, and atmosphere are initialized in unison. Support for such a system should be considered in subsequent programs of SEACI.

In conclusion, this analysis provides optimism for future direct utilization of regional climate forecasts from POAMA. In the meantime, these results provide encouragement for development of hybrid statistical-dynamical forecast schemes, whereby predictable components of the climate from POAMA that are relevant for regional Australian climate are exploited by statistical techniques to deliver useful regional predictions.

. DJF spatial	LT0	LT1	LT2	LT3	LT4	LT5	LT6
EOF1	0.95	0.93	0.93	0.91	0.91	0.91	0.91
EOF2	0.89	0.79	0.72	0.71	0.71	0.77	0.61
EOF3	0.64	0.58	0.64	0.51	0.61	0.32	0.65

DJF temporal	LT0	LT1	LT2	LT3	LT4	LT5	LT6
PC1	0.96	0.90	0.88	0.89	0.80	0.78	0.71
PC2	0.88	0.75	0.63	0.66	0.58	0.70	0.45
PC3	0.75	0.41	0.53	0.55	0.45	0.32	0.23

MAM spatial	LT0	LT1	LT2	LT3	LT4	LT5	LT6
EOF1	0.93	0.87	0.85	0.84	0.83	0.84	0.84
EOF2	0.86	0.79	0.76	0.73	0.70	0.56	0.56
EOF3	0.66	0.46	0.36	0.41	0.34	0.19	0.38

MAM temporal	LT0	LT1	LT2	LT3	LT4	LT5	LT6
PC1	0.93	0.92	0.81	0.77	0.71	0.70	0.70
PC2	0.93	0.88	0.74	0.72	0.64	0.53	0.66
PC3	0.60	0.76	0.42	0.61	0.41	0.41	0.44

JJA spatial	LT0	LT1	LT2	LT3	LT4	LT5	LT6
EOF1	0.91	0.87	0.88	0.84	0.82	0.81	0.79
EOF2	0.78	0.83	0.68	0.68	0.72	0.65	0.58
EOF3	0.09	0.02	0.12	0.26	0.24	0.38	0.11

JJA temporal	LT0	LT1	LT2	LT3	LT4	LT5	LT6
PC1	0.88	0.83	0.71	0.69	0.71	0.51	0.50
PC2	0.80	0.81	0.76	0.80	0.76	0.67	0.64
PC3	0.25	0.01	0.12	0.33	0.45	0.53	0.44

SON spatial	LT0	LT1	LT2	LT3	LT4	LT5	LT6
EOF1	0.92	0.88	0.86	0.87	0.87	0.89	0.87
EOF2	0.79	0.74	0.67	0.60	0.48	0.56	0.46
EOF3	0.47	0.32	0.34	0.25	0.43	0.38	0.12

SON temporal	LT0	LT1	LT2	LT3	LT4	LT5	LT6
PC1	0.96	0.88	0.84	0.73	0.65	0.57	0.62
PC2	0.82	0.81	0.80	0.70	0.50	0.53	0.43
PC3	0.34	0.31	0.26	0.21	0.41	0.46	0.30

Table 1. Top panel for each season is the spatial correlation of the leading 3 EOFs of SST from POAMA with that from observations, as a function of forecast leadtime. Bottom panel for each season is the temporal correlation of the predicted time variation of the leading 3 EOFS of SST from POAMA with that from observations.

DJF	LT0	LT1	LT2	LT3	LT4	LT5	LT6
PC1	0.96	0.91	0.89	0.90	0.82	0.80	0.73
PC2	0.89	0.82	0.72	0.72	0.70	0.72	0.64
PC3	0.71	0.61	0.68	0.62	0.67	0.60	0.40

MAM	LT0	LT1	LT2	LT3	LT4	LT5	LT6
PC1	0.93	0.90	0.83	0.78	0.72	0.72	0.72
PC2	0.94	0.88	0.83	0.80	0.69	0.70	0.73
PC3	0.68	0.60	0.71	0.73	0.66	0.63	0.71

JJA	LT0	LT1	LT2	LT3	LT4	LT5	LT6
PC1	0.90	0.84	0.71	0.67	0.71	0.54	0.52
PC2	0.88	0.75	0.82	0.83	0.77	0.70	0.64
PC3	0.70	0.66	0.57	0.52	0.34	0.44	0.54

SON	LT0	LT1	LT2	LT3	LT4	LT5	LT6
PC1	0.97	0.89	0.86	0.75	0.67	0.58	0.61
PC2	0.87	0.82	0.78	0.76	0.70	0.64	0.64
PC3	0.59	0.62	0.56	0.44	0.59	0.42	0.37

Table 2 Correlation between observed PCs and projections of POAMA SST onto observed EOFs

JJA	LT1	LT2	LT3	LT4	LT5	LT6	LT7
PC1	0.13	0.22	0.59	0.51	0.73	0.26	0.28
PC2	0.6	0.39	0.07	0.42	0.03	0.43	0.19
PC3	0.09	0.01	0.1	0.09	0.09	0.09	0.50

SON	LT1	LT2	LT3	LT4	LT5	LT6	LT7
PC1	0.17	0.53	0.54	0.65	0.57	0.44	0.43
PC2	0.63	0.67	0.62	0.24	0.58	0.42	0.57
PC3	0.21	0.02	0.13	0.22	0.05	0.31	0.03

DJF	LT1	LT2	LT3	LT4	LT5	LT6	LT7
PC1	0.4	0.5	0.6	0.8	0.8	0.8	0.8
PC2	0.4	0.4	0.4	0.1	0.1	0.3	0.3
PC3	0.3	0.3	0.0	0.3	0.0	0.2	0.1

Table 3 Correlation between predicted Australian-mean rainfall and principal components of leading 3 EOFs of POAMA SST, as a function of forecast leadtime.

	PC1	PC2	PC3
DJF	**-0.38**	0.12	0.07
MAM	-0.08	**-0.60**	-0.27
JJA	-0.20	-0.24	0.12
SON	**-0.47**	**-0.39**	-0.03

Table 4 Correlation of observed Australian-mean rainfall with observed EOFs of SST.

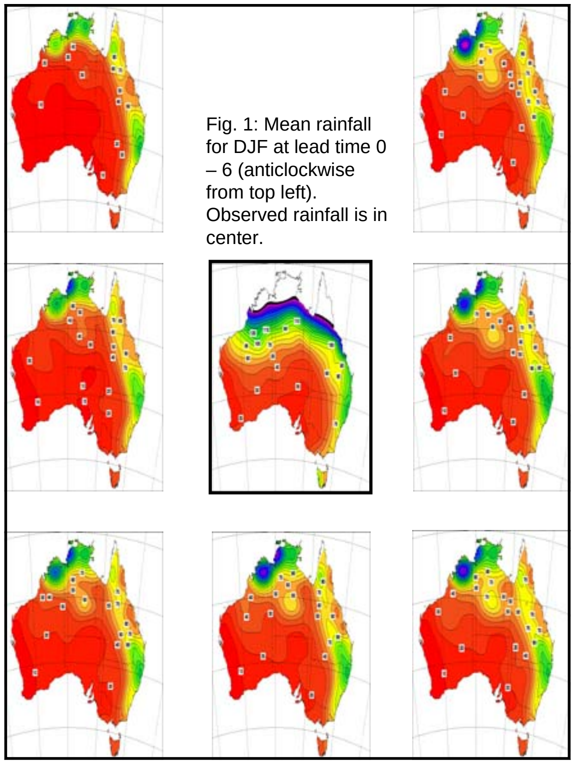

Fig. 1: Mean rainfall for DJF at lead time 0 – 6 (anticlockwise from top left). Observed rainfall is in center.

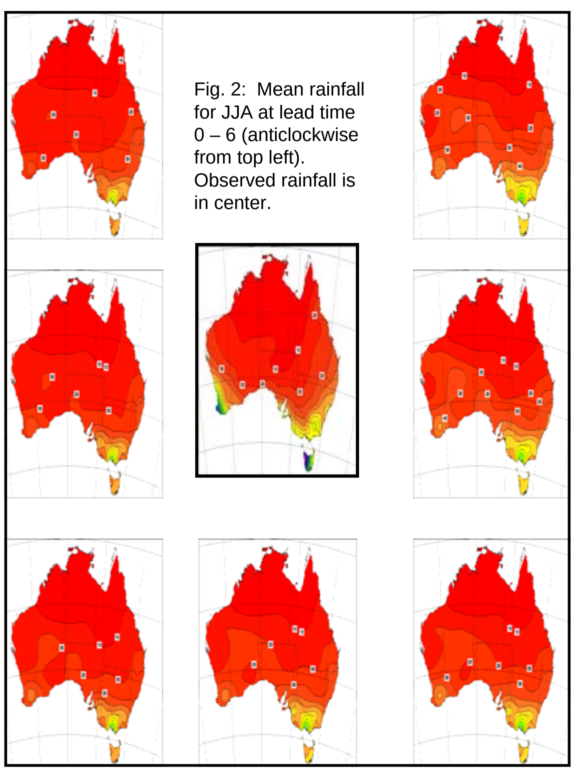

Fig. 2: Mean rainfall for JJA at lead time 0 – 6 (anticlockwise from top left). Observed rainfall is in center.

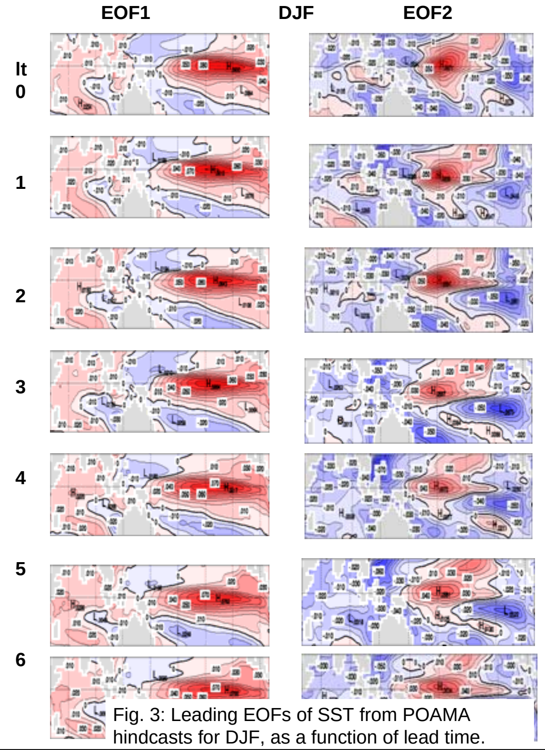

Fig. 3: Leading EOFs of SST from POAMA hindcasts for DJF, as a function of lead time.

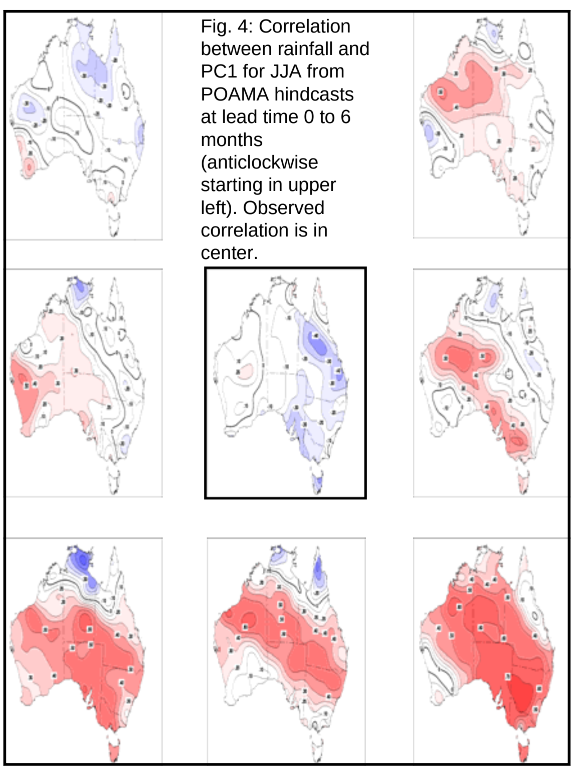

Fig. 4: Correlation between rainfall and PC1 for JJA from POAMA hindcasts at lead time 0 to 6 months (anticlockwise starting in upper left). Observed correlation is in center.

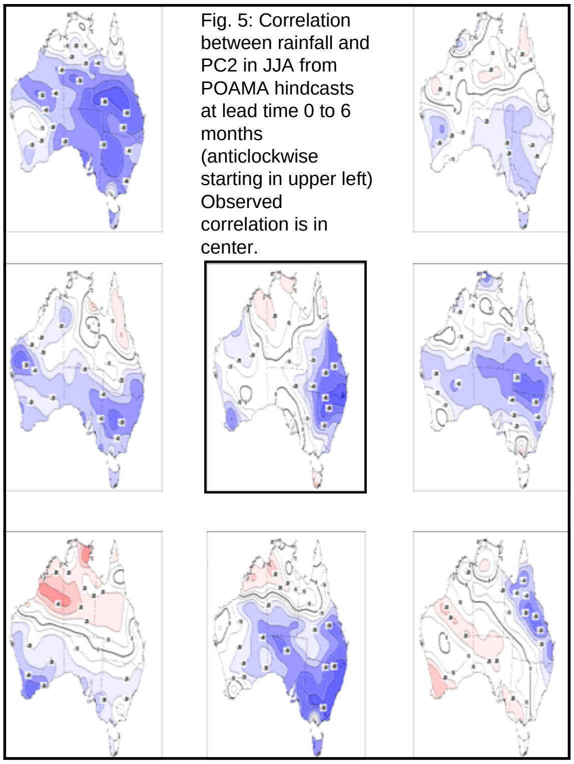

Fig. 5: Correlation between rainfall and PC2 in JJA from POAMA hindcasts at lead time 0 to 6 months (anticlockwise starting in upper left) Observed correlation is in center.

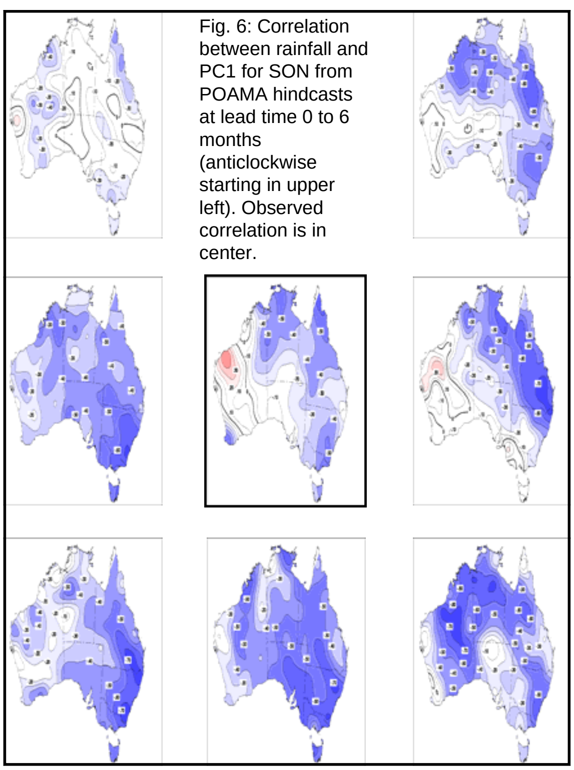

Fig. 6: Correlation between rainfall and PC1 for SON from POAMA hindcasts at lead time 0 to 6 months (anticlockwise starting in upper left). Observed correlation is in center.

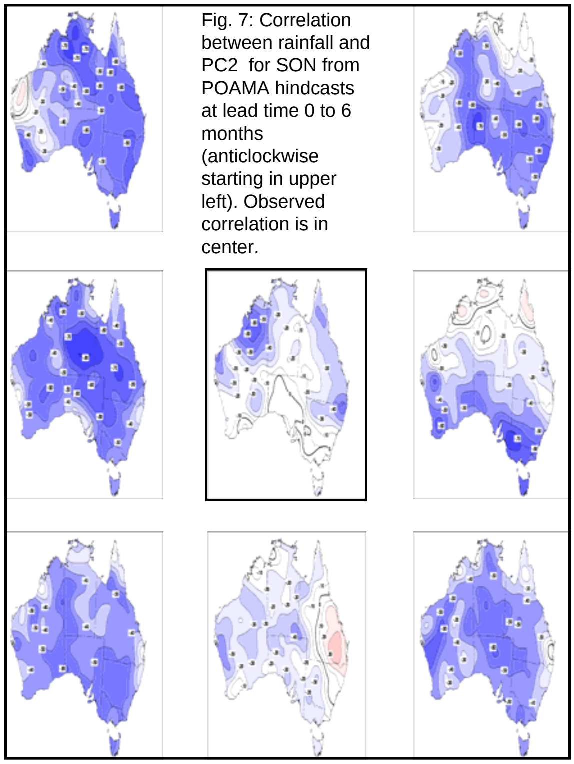

Fig. 7: Correlation between rainfall and PC2 for SON from POAMA hindcasts at lead time 0 to 6 months (anticlockwise starting in upper left). Observed correlation is in center.

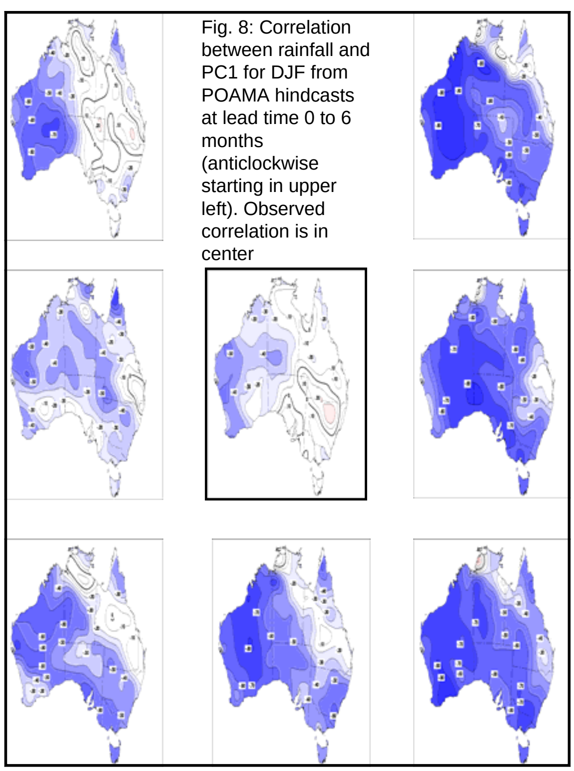

Fig. 8: Correlation between rainfall and PC1 for DJF from POAMA hindcasts at lead time 0 to 6 months (anticlockwise starting in upper left). Observed correlation is in center

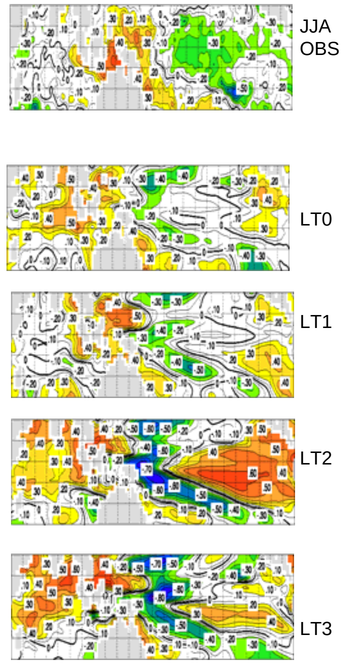

Fig. 9
Correlation
SEACI-mean
rainfall with SST
for JJA season

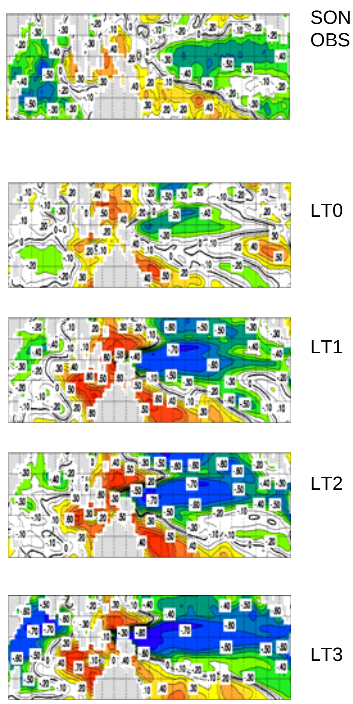

Fig. 10
Correlation
SEACI-mean
rainfall with
SST for SON
season

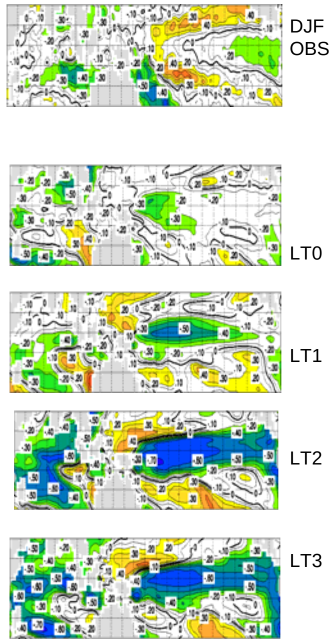

Fig. 11 Correlation SEACI-mean rainfall with SST for the DJF season