



South Eastern Australian Climate initiative

Final report for Project 3.1.2P

Assessment of improved POAMA forecasts for hydrologically relevant surface variables

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Abstract

An improved version of the Bureau's coupled dynamical seasonal forecast model (Predictive Ocean-Atmosphere Model for Australia – POAMA2) is being developed, which will be used to make improved predictions of hydrologically relevant surface fields for south-eastern Australia (SEA). The improved version of POAMA2 includes reduced mean state drift, improved coupling, new ocean data assimilation, new atmosphere and land initialisation and higher horizontal resolution, which will benefit regional climate prediction. Limited hind-cast sets were generated and the impact of the reduced mean state drift on El Niño variability, predictive skill of El Niño and on the El Niño teleconnections into Australia has been assessed. The outcome of this study will then guide the final configuration of POAMA2. Full details of this project are provided in the technical report by Lim et al. 2009 (attached).

Project Objectives:

- Determine impact of improved POAMA mean state on simulated El Niño variability, predictive skill of El Niño (including inter-El Niño variability), and on teleconnections of El Niño into SE Australia.
- Recommend options for final configuration of POAMA2

Significant research highlights, breakthroughs, and snapshots

- Flux-correction in a version of POAMA2 was able to significantly reduce the main model bias that plagued POAMA1.5b at longer lead time (i.e. flux-correction nearly eliminated the generally cold tropical bias and it eliminated the bulk of the warm bias in the upwelling region off of the west coast of South America)
- The patterns of sea surface temperature (SST) variability associated with El Niño were more realistic at all lead times in the flux-corrected version as compared to the non-flux corrected version of POAMA2.
- The teleconnection of El Niño to regional climate in SEA was improved, especially at longer lead time, in the flux corrected version of POAMA2 compared to the non-flux corrected version of POAMA2.
- Predictive skill of rainfall in SEA was improved at longer lead time in the flux-corrected version of POAMA2 compared to the non-flux corrected version, which is attributed to the improved representation of the teleconnection of El Niño.
- However, predictions of rainfall for SEA from the experimental flux corrected version of POAMA2 were generally less skilful than from the older POAMA1.5b at the shortest lead time, which may stem from degraded atmospheric initial conditions (the nudging in ALI was once per day for POAMA2 while it was every six hrs for POAMA1.5b). It may also reflect use of a small ensemble (only five members). A detailed investigation is now underway by re-doing the POAMA2 forecasts with six-hourly nudged ALI initial conditions and by creating a larger ensemble.
- Flux-correction (reduction of mean-state bias) appears to have significant merit and should be considered as a viable option, at least in combinations of other model versions, for the final version of POAMA2

Statement of results, their interpretation, and practical significance against each objective

Here we provide some detail of the generation of forecast from the experimental versions of POAMA2. The forecasts analysed here are from two experimental versions of POAMA2. Compared to POAMA1.5b, these are run at a higher horizontal resolution in the atmosphere (T63 compared to T47) and have an improved ocean assimilation system (PEODAS compared to PODAS). 5-member ensemble hindcasts were generated from 3 different initial times – 1st of March, 1st June and 1st September for the two versions of the model. Forecasts were initialized for 1982-2006. The two model versions are with and without flux correction. The results in this report are based on the forecasts that verify in June-July-August (JJA) initialized on the 1st of June (lead time 0, LT0) and on the 1st of March (lead time 3 months, LT3). SST and rainfall hindcasts were verified against Reynolds SST for the period of 1982-2006 and National Climate Centre (NCC) gridded rainfall analyses for the period of 1980-2006 (Jones and Weymouth 1993).

Two major changes from POAMA1.5b are increased horizontal resolution (T63 vs T47) and the method to generate ocean initial conditions through a new state-of-the-art, ensemble-based ocean data assimilation scheme called the POAMA Ensemble Ocean Data Assimilation System, PEODAS. A unique feature of PEODAS is that an ensemble of ocean states is generated, which reflects observational uncertainty and which can be used as perturbed initial conditions that are needed to generate ensemble forecasts (Alves et al. 2009). In order to explore the impact of mean state bias on regional climate predictions at longer lead time, several attempts were made in POAMA2 to reduce mean state bias that were prominent in POAMA1.5b. Firstly, a newer version of the atmospheric component includes improved physics (including a bug fix from a previous version in the shallow convection scheme) and higher horizontal resolution (~ 200 km horizontal resolution). A flux-correction to alleviate the remaining SST bias (i.e. the tropical wide cold bias and a strong regional warm bias off of S. America) was applied. This scheme corrects the SST mean state bias by correcting biases in short wave radiation, total heat flux, and wind stress. The resulting model is referred to as POAMA 2.1f.

Flux correction can produce meaningful reduction in mean state bias in SST at longer forecast lead times. Reduction in mean state bias had little impact on the ability to predict the occurrence of El Niño. However, the reduction in bias results in an improved representation of the spatial patterns of SST associated with El Niño and an improved representation and prediction of El Niño-impacts during winter in SEA. Bias correction, via flux-correction, would appear to be a viable solution for improving regional rainfall forecast skill at longer lead time and should be considered as an option for implementation of POAMA2. Nonetheless, flux-correction is not an ultimate solution, and work should continue to improve both the depiction of the mean state and the variability associated with El Niño in the POAMA forecast model.

Acknowledgement

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Lim, E., H. Hendon, O. Alves, Y. Yin, M. Zhao, G. Wang, D. Hudson, and G. Liu 2009: Impact of SST bias correction on prediction of ENSO and Australian winter rainfall. SEACI Technical Report, Milestone 3.1.2P

Attachment

Impact of SST bias correction on prediction of ENSO and Australian winter rainfall

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1. Introduction

The Bureau of Meteorology (BoM) jointly with the Commonwealth Scientific and Industrial Research Organization (CSIRO) has developed a coupled atmosphere-ocean climate prediction system, POAMA (Predictive Ocean Atmosphere Model for Australia) in order to improve the quality of seasonal climate forecasts over Australia. A primary focus for POAMA is the prediction of sea surface temperature (SST) anomalies associated with El Niño/La Niña, whose occurrence and detailed spatial structure significantly impact Australian climate variability (McBride and Nicholls 1983, Wang and Hendon, 2007). Based on 10 member ensemble hindcasts from POAMA1.5b for the period 1980-2006, the skill to predict the occurrence of El Niño/La Niña is internationally competitive (Wang et al. 2008), and different spatial characteristics, or “different flavours” of each El Niño/La Niña are also predictable up to a season in advance (Lim et al. 2007). Furthermore, Lim et al(2009a, 2009b) show that from autumn to spring, especially over south eastern Australia, POAMA can provide skilful seasonal forecasts of rainfall and maximum temperature that are competitive with the NCC operational statistical model (Drosowsky and Chambers 2001).

Despite these positive outcomes from POAMA, the simulated mean state drifts through the nine-month forecast cycle: SST is simulated to be colder than observed over most of the tropics and subtropics and is too warm off the west coast of South America. These biases in the mean state impact the simulated/forecast SST variability associated with ENSO (El Niño and the Southern Oscillation). For instance, a direct result of the cold bias in the equatorial Pacific is that the maximum ENSO variability in SST shifts westward away from the South American coast with increasing lead time. Such drift in the SST variability hinders the model’s ability to discern differences in SST patterns between ENSO events at longer lead times (Lim et al. 2007, Lim et al. 2009b). Furthermore, the teleconnection between ENSO and Australian climate is also adversely affected by these model bias and drift. For example, the relationship between ENSO and Australian winter rainfall is oppositely simulated to the observed relationship with lead times longer than a couple of months (Hendon et al. 2007). Hence, mean-state drift in POAMA is hindering the ability to capitalize on POAMA’s ability to make extended range prediction of El Niño for regional climate predictions in SE Australia. The aim of the present study is to attempt to correct the model SST bias and drift using flux correction, and then assess the impact on prediction skill of ENSO and its teleconnection to SE Australia. Ultimately, then, this study is aimed at trying to improve longer lead forecasts of regional climate in SE Australia.

We describe the POAMA model configurations, the method of flux correction, the forecast generation, and the verification methods in Section 2. In Section 3 we re-examine the main characteristics of tropical Indo-Pacific SST variability and their association with Australian rainfall in winter in the observation. Then, we assess the forecast skill for ENSO and Australian rainfall in the non-flux

corrected versus flux corrected versions of POAMA. Finally, concluding remarks will be given in Section 4.

2. Configuration of experimental POAMA2

The forecasts analysed here are from POAMA2, which is based on version 3.0 of the Bureau of Meteorology's Atmospheric Model (BAM; Colman et al. 2005) coupled to version 2 of the Australian Community Ocean Model (ACOM2; Schiller et al. 2002). The atmospheric model is run with modest horizontal resolution (~ 300 km resolution) and with 17 vertical levels (T47L17). The ocean model is run with ~ 200 km zonal resolution and telescoping meridional resolution to 0.5° latitude in the tropics (i.e. the meridional resolution gradually decreases from the poles towards the tropics).

For this study, five-member ensemble hindcasts were generated from three different initial times – 1st of March, 1st June and 1st September. We will focus on the forecasts that verify in June-July-August (JJA) initialized on the 1st of June (lead time 0, LT0) and the 1st of March (lead time three months, LT3). SST and rainfall hindcasts were verified against Reynolds SST for the period of 1982-2006 and National Climate Centre (NCC) gridded rainfall analyses for the period of 1980-2006 (Jones and Weymouth 1993).

A major change made in POAMA2, compared to POAMA1.5b, was to generate ocean initial conditions through a new state-of-the-art, ensemble-based ocean data assimilation scheme called the POAMA Ensemble Ocean Data Assimilation System, PEODAS. An ocean reanalysis with PEODAS for the period 1980-2007 has now been completed, and these re-analyses have been used to initialise the five-member ensemble for 1980 to 2006. A unique feature of PEODAS is that for any point in time it produces an ensemble of ocean states, rather than one, that represents observational uncertainties. This ensemble of states was used to generate the perturbations for the coupled model ensemble (Alves et al. 2009).

In addition to PEODAS, several attempts have been made in POAMA2 in order to reduce mean state bias that were prominent in POAMA1.5b: Firstly, a newer version of BAM (v3.1) that includes improved atmospheric model physics (including a bug fix from Bam3.0 in the shallow convection scheme) and higher horizontal resolution (~ 200 km horizontal resolution) was coupled to ACOM2 (POAMA 2.1a). Then, a flux-correction to alleviate the SST bias was applied to POAMA 2.1a (POAMA 2.1f). This scheme corrects the SST mean state bias by correcting biases in short wave radiation, total heat flux, and wind stress. As the only difference between POAMA 2.1a and 2.1f is the use of the flux correction scheme, comparison between POAMA 2.1a and 2.1f can show the sensitivity of forecast skill to the explicit correction of the SST mean bias.

The resultant SST differences in the climate of the forecasts between different versions of POAMA and the observation (Reynolds et al. 2002) are displayed in Figure 1. The improved model physics alone reduces the cold bias significantly (i.e., POAMA 2.1a vs. POAMA 1.5b). As expected, the flux correction scheme further reduces both the prominent cold and warm biases (POAMA 2.1f), with the cold bias across the Tropics now being less than 1.5 °C and the warm bias off of South America being reduced to less than 4 °C.

3. Results

3.1 Observed relationship between ENSO and Australian rainfall in winter

Prior to discussing impact of prediction skill of the new versions of POAMA for ENSO and Australian rainfall, the observed relationship between ENSO and rainfall in the last three decades is first reviewed. We begin by considering the relationship between the leading modes of tropical SST and rainfall. The leading modes of SST variability are identified with EOF analysis over the domain of 30°S-20 °N, 40°-280°E. The spatial patterns of the first two EOF modes are displayed as the regression of SST anomaly onto the principal component time series (PCs) and are scaled for a 1-standard deviation anomaly of the PCs (Fig. 2a, b). Hereafter, these regression patterns are referred to as the EOFs. The spatial pattern of the first EOF mode represents canonical mature ENSO conditions (e.g. Trenberth 1997), with maximum loading over the equatorial eastern Pacific. This mode explains 40 per cent of the SST variance in winter. The second EOF mode (Fig. 2b) depicts east-west variations of each ENSO event (e.g. Trenberth and Stepaniak 2000, Wang and Hendon 2007). Previous studies have suggested that El Niño events that have maximum SST anomaly over the central Pacific (i.e. events that have positive EOF2 in conjunction with positive EOF1; Trenberth and Stepaniak 2000, Ashok et al. 2007) tend to have more significant impact on regional climate over the Pacific rim countries (Hoerling and Kumar 2002, Kumar et al. 2006, Wang and Hendon 2007; Weng et al. 2007). EOF2 accounts for 18 per cent of the total SST variance, which is much less than for EOF1, but its loadings in the central Pacific are in a region of warm background SST, hence they can be associated with large atmospheric response.

The two leading modes of SST variability are both associated with winter rainfall variability over eastern Australia (Fig. 2c). Together SST EOF1 and EOF2 can account for 20-40 per cent of the total rainfall variance over the eastern states. However, the 2nd EOF of SST accounts for more winter rainfall variance than the first especially over Queensland and New South Wales. This finding is also confirmed by the stronger correlation of eastern Australian-mean rainfall (land points east of 140 °E) with SST PC2 (-0.5) than with SST PC1 (-0.3).

3.2 Impact of reduced mean bias in SST on the predictions of ENSO and associated Australian rainfall

In light of this updated understanding of the relationship between different flavoured ENSO events and Australian rainfall in winter, we first examine the sensitivity of POAMA to simulate the leading two modes of Indo-Pacific SST as a result of reduction in mean-state bias. We then assess the sensitivity to reduction of mean state bias for skill of predicting the leading two modes of SST.

We first assess how well POAMA simulates the spatial pattern of SST associated with the leading two modes of tropical SST. We do this by computing the spatial correlation between the observed and simulated leading modes of SST (Table 1). In POAMA1.5b, the simulated EOF1 is more strongly correlated with the observed than is EOF2. And, while the correlation for both the first and second EOF drops off with increasing lead time, it drops off much quicker for EOF2. Similar behaviour is apparent for POAMA2.1a. In contrast, in the flux corrected version (POAMA2.1f), both the initial pattern correlations are higher and the drop off at longer lead time is reduced compared to the non-flux corrected version. This is an encouraging result that indicates a potentially significant benefit of reduction of mean-state bias for regional climate prediction: reduced bias in the ENSO mode should result in reduced bias in the ENSO teleconnection. We confirm this result after first assessing the impact of reduced mean state bias on prediction of ENSO.

Assessment of the prediction of SST EOFs 1 and 2 was undertaken by projecting forecast maps of SST onto the observed EOF patterns shown in Figure 2, thus resulting in predictions of temporal loading

coefficients (the PCs). Skill is assessed using temporal correlation and normalized root-mean-square-error (NRMSE; i.e., forecast RMSE normalized by the standard deviation of the corresponding observed PC time series). According to Figure 3, both non-bias corrected and bias corrected versions of POAMA can skilfully predict SST PC1 and PC2 up to a season in advance (correlation > 0.6 and NRMSE < 1). Although, reduction of mean-state bias appears to have improved the simulation of the ENSO modes in POAMA (Table 1), the effect of bias correction is not pronounced on the skill of predicting the leading pair of SST (although there is some indication of reduced skill for EOF1 in the flux-corrected version at longer lead times). The bias correction does appear to result in an increase of the ensemble spread for predicting PC2, which is a positive benefit because POAMA suffers from being overconfident (i.e. too low spread).

A major deficiency of POAMA1.5b (non-flux corrected) was the development of the wrong sign of teleconnection between leading EOF of SST and eastern Australian rainfall at longer lead time. This error prevented POAMA from making skilful predictions of regional rainfall in Australia at longer lead time despite the ability to predict El Niño at longer lead time. This problem still exists for the POAMA 2.1a forecasts (Fig.4a): Although POAMA2.1a simulates a realistic negative relationship between PC1 and Australian rainfall in the east at LT 0 (compare Fig. 4a to Fig. 2) , the relationship erroneously changes sign by LT 3. In POAMA 2.1f with bias correction, the erroneous teleconnection between PC1 and rainfall is much reduced, with the correct sign of the relationship now found in the far eastern side of the country at LT 3 (Fig. 4b). Also, the stronger relationship of eastern Australian rainfall with PC2 than with PC1 in the observation is well represented at three-month lead time in POAMA 2.1f. In summary, the flux corrected version of POAMA, while not providing any better skill in predicting ENSO related SST variations, does better represent the teleconnection of El Niño to east Australian rainfall.

Our final question, then, is whether this improvement in teleconnection at longer lead time transfers to the improved skill in predicting regional rainfall. Figure 5 displays correlation of rainfall predicted in POAMA 2.1a and POAMA 2.1f. At LT 0, forecast skill of the two versions is not very different to each other over most of Australia (but, unfortunately they are both slightly worse than from POAMA1.5b), but at LT 3 the flux corrected forecasts show much improved skill in the eastern Australia. This is the region where the teleconnection to ENSO has been improved.

4. Concluding remarks

We have briefly re-examined the relationship between different types of El Niño events and Australian rainfall in the winter season and have investigated whether reduction of SST bias in the Bureau of Meteorology's dynamical coupled seasonal forecast model can improve skill for prediction of ENSO and its teleconnections to Australian rainfall. Observed Australian winter rainfall variability, especially over the east, is strongly associated with both traditional El Niño events that have peak SST warming in the eastern Pacific, and El Niño events that have peak warming in the central Pacific. In winter, a larger portion of eastern Australian rainfall variance is explained by the 2nd SST EOF whose maximum SST variability is located far westward of that the 1st SST EOF. Previous versions of POAMA can skilfully predict some of these different patterns of SST during El Niño, but regional prediction of rainfall in eastern Australia is hindered at longer lead time because of an erroneous depiction of the teleconnection between eastern Pacific El Niño events and rainfall at longer forecast lead times. This degradation of the teleconnection was attributed to mean state drift in the earlier version of POAMA.

Our results have shown that the first two dominant EOF modes of tropical SST are skilfully predicted by a new version of POAMA2 in both non-bias corrected and bias corrected versions (POAMA 2.1a and 2.1f, respectively). However, the impact of reducing SST bias on forecast skill for the patterns of

SST associated with EOFs 1 and 2 is not clear. Reduction of mean state bias does improve the model's simulation of pattern of SST variability associated with the leading two modes of SST and it does improve the teleconnection to eastern Australia rainfall. But, the skill in predicting the temporal evolution of these two modes shows little sensitivity to bias correction. The improvement in depicting the spatial pattern of SST variability associated with the first two modes does carryover to an improved depiction of the teleconnection from El Niño and increased skill for predicting rainfall at longer lead time over eastern Australia. While not solving all the problems of predicting ENSO and its regional impacts in SEA, bias correction would appear to be a viable solution for improving rainfall skill at longer lead time and should be considered as an option for implementation of POAMA2.

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EOF1	LT 0	LT 3
POAMA 1.5b	0.92	0.89
POAMA 2.1a	0.93	0.89
POAMA 2.1f	0.95	0.91

EOF2	LT 0	LT 3
POAMA 1.5b	0.85	0.58
POAMA 2.1a	0.84	0.66
POAMA 2.1f	0.87	0.76

Table 1: Pattern correlation of observed and predicted 1st and 2nd EOFs of tropical Pacific SST.

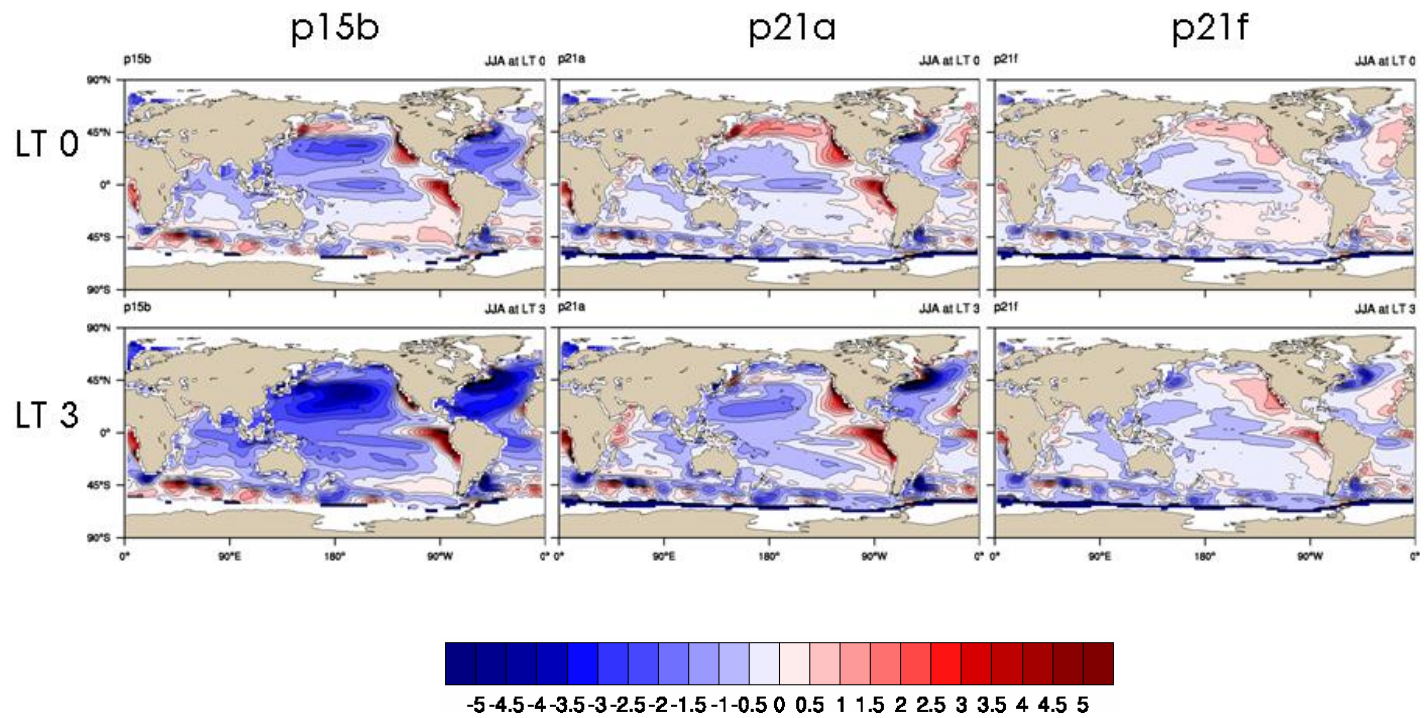
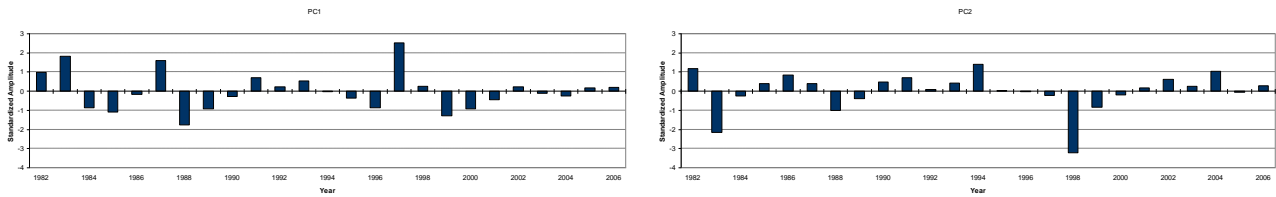
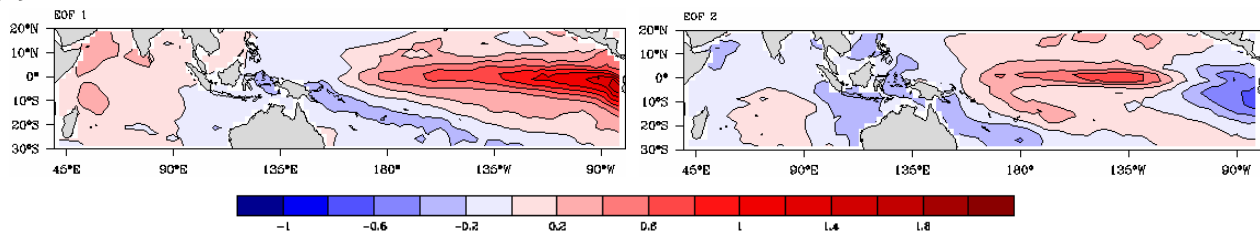


Figure 1: Difference between the mean predicted SST and observed mean SST in the austral winter as a function of lead time. Positive (negative) values mean that POAMA predicts higher (lower) SST than observation on average. The contour interval is 0.5 °C.

(a)



(b)



(c)

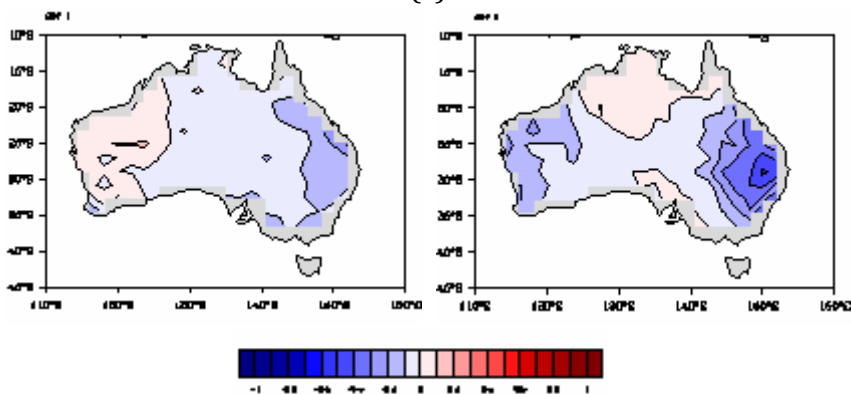


Figure 2: Dominant EOF modes of SST variability and the associated Australian rainfall component: (a) Standardized 1st (left panel) and 2nd (right panel) principal component time series (PCs) of tropical Indo-Pacific SST variability in JJA, (b) regression patterns of SST onto the standardized PCs, and (c) regression patterns of Australian rainfall onto the standardized PCs. The contour interval is 0.2 °C per standard deviation of the respective PC in (b) and 0.1 mm per day per standard deviation of the respective PC in (c).

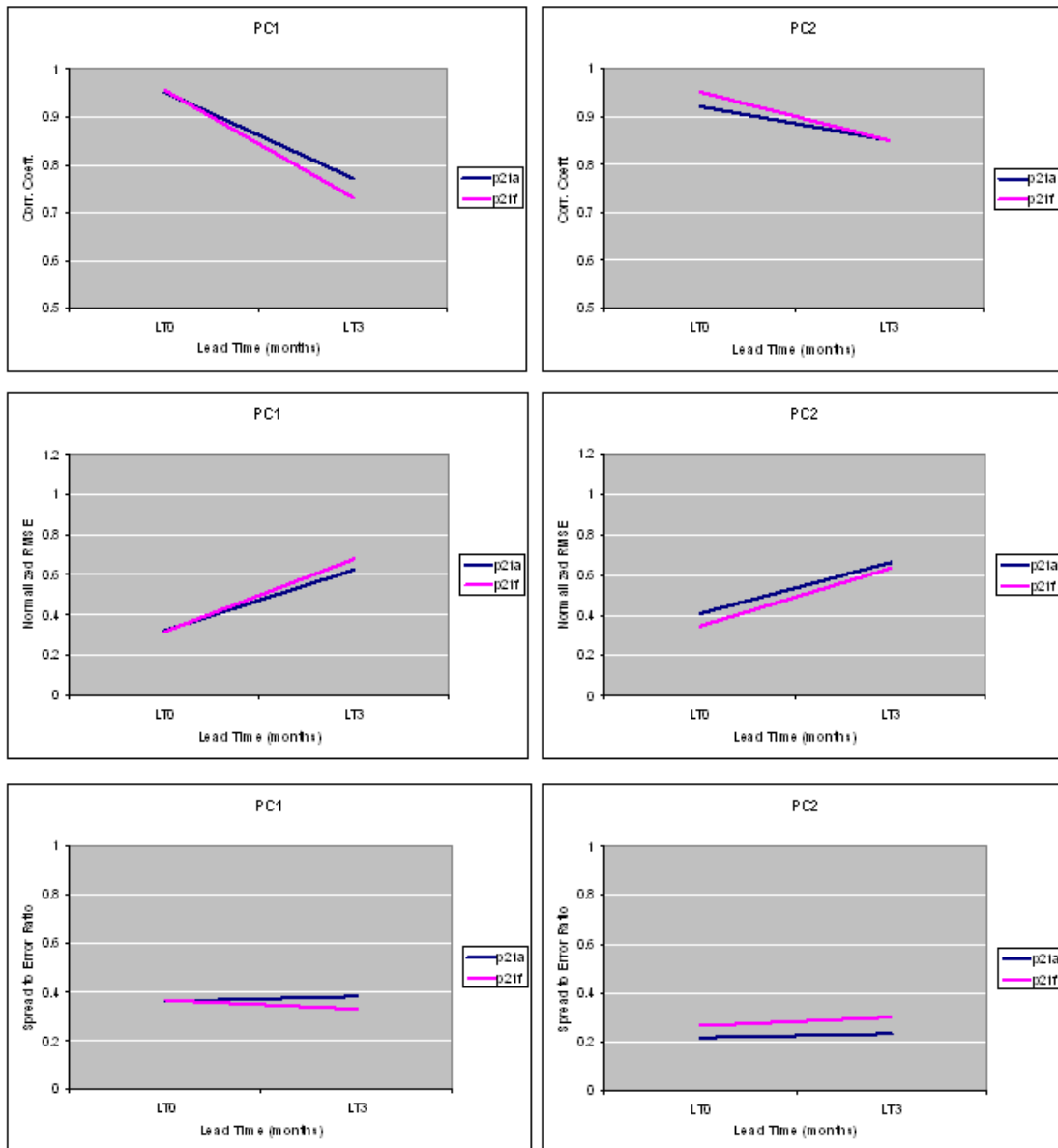


Figure 3: Correlation, normalized root-mean-square-error (RMSE) of ensemble mean predictions and ratio of ensemble spread to the RMSE of ensemble mean prediction of SST PC1 (left panels) and PC2 (right panels) from POAMA 2.1a (blue lines) and POAMA 2.1f (pink lines). The RMSE of each PC was normalized by the standard deviation of the observed counterpart.

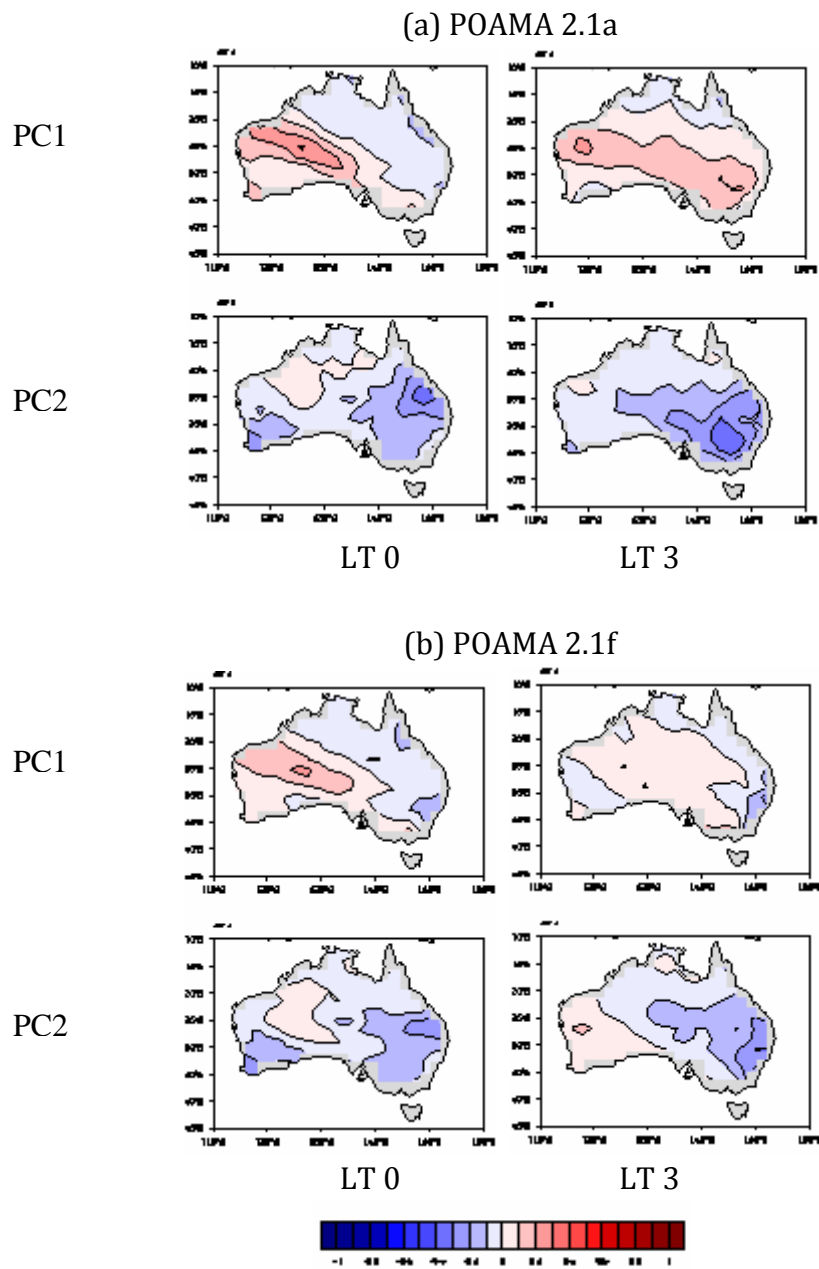


Figure 4: Regression of predicted rainfall onto the predicted PCs of observed EOF1 and EOF2 in POAMA 2.1a and POAMA 2.1f. The contour interval is 0.1 mm per day per standard deviation of each PC time series.

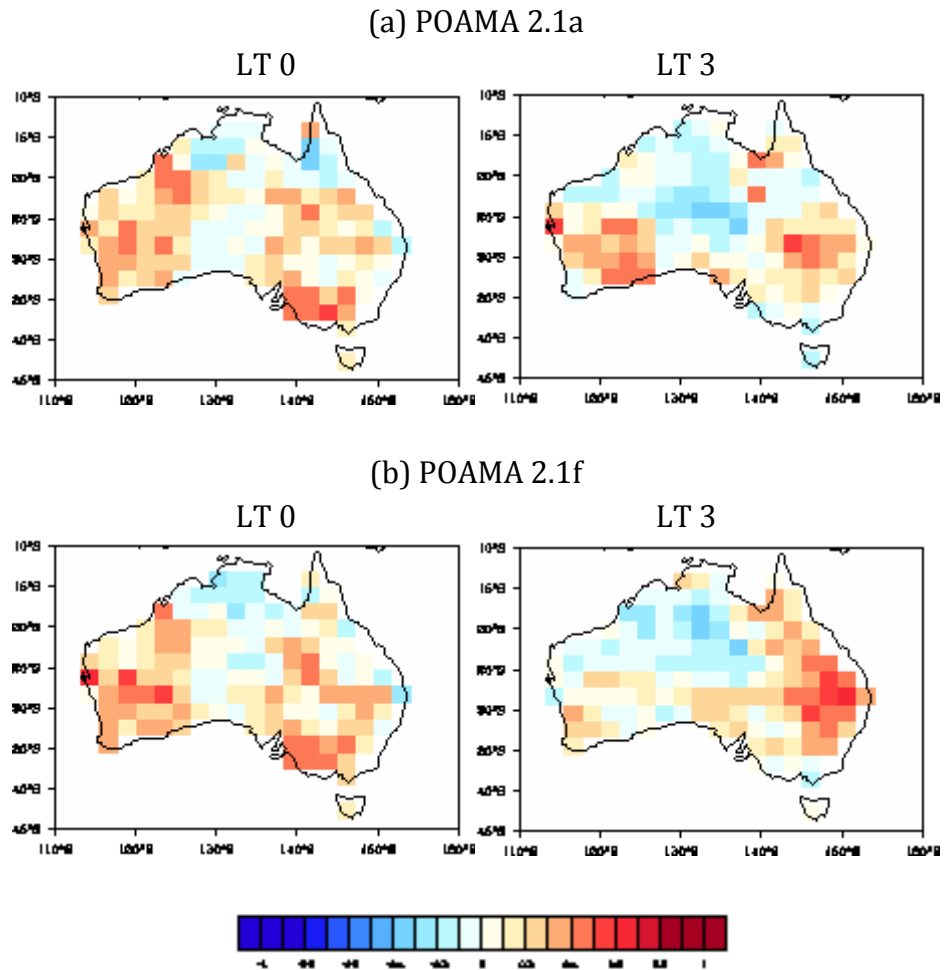


Figure 5: Correlation of predicted rainfall in the non-flux corrected (POAMA 2.1a) and flux corrected (POAMA 2.1f) versions of POAMA at lead time zero and three months. The contour interval is 0.1.