

Figures



South Eastern Australian Climate initiative

Final report Project 3.2.2

**Review of techniques to bridge/calibrate
dynamical seasonal predictions with focus on
south eastern Australia**

Principal Investigator: Drs. Harry Hendon and Oscar Alves

Bureau of Meteorology Research Centre (BMRC), email: hhh@bom.gov.au,
Tel: 03-9669-4120, Fax: 03-9669-4660, GPO Box 1289, Melbourne 3001

Co-Authors: Drs. Eun-Pa Lim and Guomin Wang

Bureau of Meteorology Research Centre (BMRC), email: e.lim@bom.gov.au,
Tel: 03-9669-4636, Fax: 03-9669-4660, GPO Box 1289, Melbourne 3001

Completed: 16 November 2007

Abstract

The Bureau of Meteorology routinely issues real-time forecasts for tropical sea surface temperature with up to 8 month lead time using the Predictive Ocean Atmosphere Model for Australia (POAMA). Regional climate forecasts from models such as POAMA are hindered by model bias and spatial scale that is too coarse for many applications. Therefore, we have reviewed and investigated the utility of simple statistical schemes for relating regional scale rainfall and temperature to forecasts of climate variables from POAMA.

Statistical-dynamical forecasts capitalize on the components of the climate system for which POAMA provides skilful prediction and which have a strong association with Australian climate. Because statistical post-processing itself cannot generate skill, the dynamical model must have skill in predicting some aspects of the climate. A 3 member ensemble hindcast from POAMA v. 1.5 was examined to determine the predictable components of climate variability that are related to south eastern Australian rainfall variability. The first few dominant modes of tropical Indo-Pacific SST variability, which explain up to 1/2 of Australian rainfall variability (depending on season), are predictable by POAMA at lead time up to 2 seasons. Furthermore, POAMA also demonstrates reasonable skill in directly predicting Australian rainfall at short lead times. Together, these findings suggest the possibility to improve regional forecast skill for Australian rainfall through statistical-dynamical prediction by using POAMA's SST forecast (bridging) or POAMA rainfall forecast (calibration). Preliminary analysis of the POAMA hindcasts indicates skilful prediction for below/above median rainfall for south eastern Australia at lead times out to 2 seasons, and further skill improvement is obtained from statistical-dynamical calibration and bridging. However, skilful prediction by dynamical and statistical-dynamical models varies for different regions in different seasons.

Significant research highlights, breakthroughs and snapshots

- POAMA demonstrates skill in predicting tropical Indo-Pacific SST (lead times to 6-9 months) and Australian rainfall (lead time to ~3 months) with 3 member ensemble hindcasts in 1980-2005.
- Statistical bridging/calibration schemes were developed and found to be able to extend POAMA's forecast skill for south eastern Australian rainfall.
- 10 member ensemble hindcasts from 1980 to 2006 have been generated in order to reduce noise and improve reliability.
- Current Australian rainfall and temperature real-time forecasts are available at POAMA official website : <http://poama.bom.gov.au/>

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

- **Project objectives:** Review and identify possible statistical methods to improve direct prediction of rainfall and temperature from the Bureau's dynamical seasonal forecast model (POAMA)

1) Review of statistical-dynamical techniques

The basic approach of all statistical post-processing techniques is to develop relationships between forecasts and verification in a training period, and then to apply the statistical relationship to extend model forecasts for independent periods. In general, there are two ways to design statistical-dynamical prediction schemes: One is to relate forecasts of large-scale features from a dynamical model to regional scale climate variable (statistical bridging - e.g. use tropical SST predicted from POAMA to predict south eastern Australian rainfall based on their observed relationship). The other is to adjust patterns of regional forecasts from the dynamical model against observations in order to remove systematic bias (statistical calibration – e.g. POAMA rainfall forecasts across Australia to observed Australian rainfall). In these methods, predictors (e.g. POAMA SST or POAMA rainfall) must be fields for which the model has predictability, and predictands (e.g. observed rainfall) must have a robust statistical relationship with the predictors.

Common approaches to identifying a statistical relationship of the predictors and predictands include singular value decomposition analysis (SVDA), canonical correlation analysis, or principal component analysis. These techniques expand predictors and predictands in terms of dominant patterns of variability and the time series of those patterns (Bretherton et al. 1992, Ward and Navarra 1997, Feddersen et al. 1999). In this project SVDA was adopted as it provides a direct measure of association between a predictor and a predictand, and its computation is straightforward.

Once the major analysis tool is chosen, the rest of the processes to form a statistical-dynamical prediction scheme are as follows: First the times series of the dominant spatial patterns of the predictor are regressed on the time series of the predictand by a multiple linear regression scheme in a training period. This regression relationship is used to make forecasts of a predictand in an independent period. For more details of the analysis tools and computing processes, refer to Hendon et al. (2007).

2) Identification of predictable climate components by POAMA

According to Wang and Hendon (2007), about 50% of eastern Australian spring rainfall was explained by the leading three spatial patterns (Empirical Orthogonal Function, EOFs) of tropical Indo-Pacific SST in 1982-2002. Wang and Hendon (2007) emphasized that Australian rainfall is not only sensitive to the leading pattern (EOF1) that represents mature ENSO condition, but also to the second and third EOFs which represent east-west shifts of equatorial east Pacific SST that occur in individual El Niño events. Our investigation with an extended observed data record (1980-2006) demonstrated that the temporal variations of the first 4 EOFs of SST can explain up to 50% of the rainfall variability in the south eastern part of the country (SEACI region, 38.5°-33.5°S, 137.5°-152.5°E; Fig. 1).

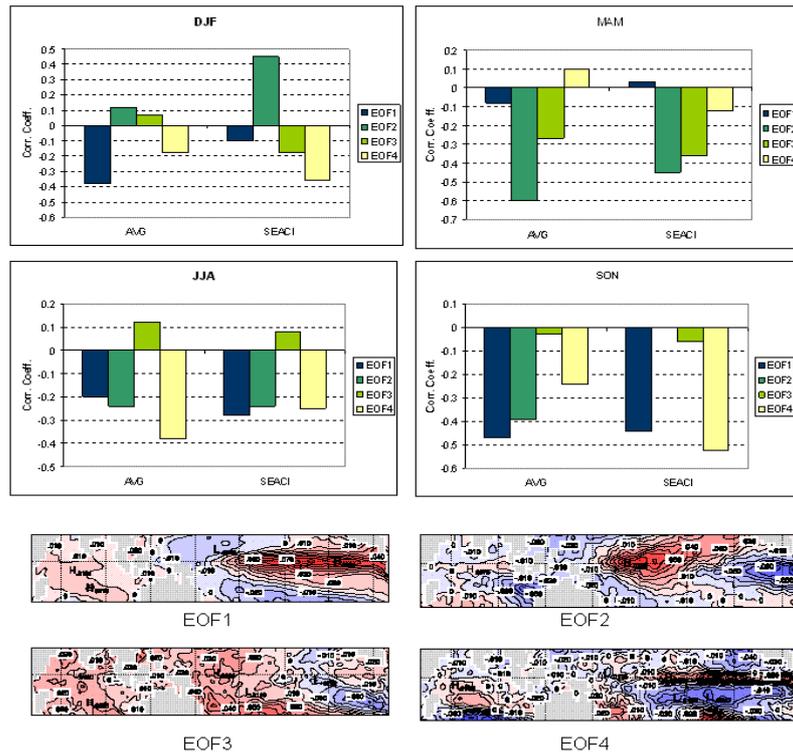


Figure 1: Correlation of observed south eastern Australian rainfall and the time series of the first four leading EOF modes of tropical Indo-Pacific SST variability (histograms). The spatial patterns of the four leading EOF modes of tropical SST are displayed with maps.

Given the observed relationship between the tropical Indo-Pacific SST and Australian rainfall, it is important to address whether POAMA can predict the temporal variations of the leading patterns of tropical SST variability. Our study reveals that the first few EOF time series of SST predicted from POAMA are highly correlated with their observed counterparts with lead times of up to a season (refer to Table A-1 in Appendix for correlation coefficients). POAMA's predictions of the first two dominant modes of SST readily beat persistence in all seasons except for autumn at 3 month lead time. Therefore, POAMA has good skill in predicting not only the occurrence of El Niño/La Niña, but also some of the important variability of SST between ENSO events with lead time of a few months.

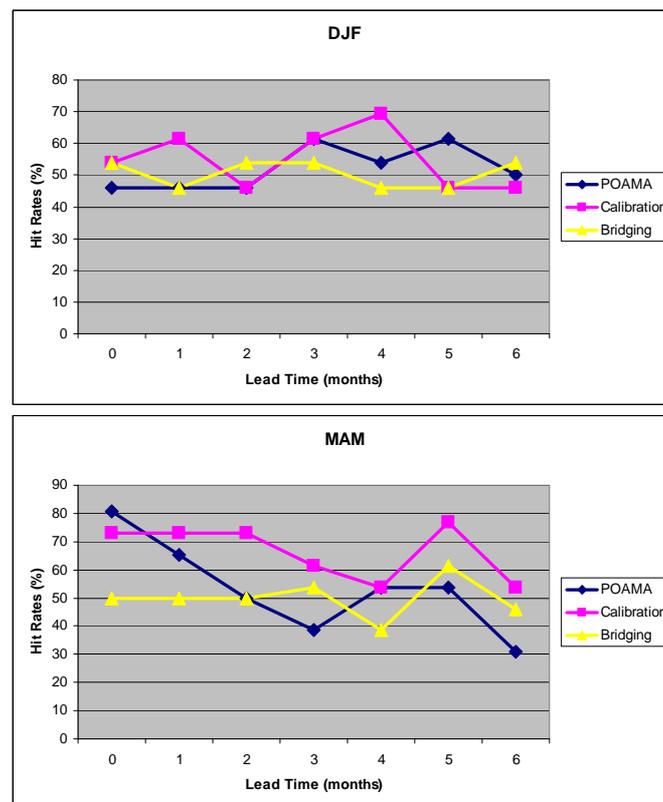
On the other hand, POAMA shows moderate skill in direct prediction of Australian rainfall. The correlation between POAMA's prediction at lead time 0 (lead 0 means, for instance, a forecast for JJA that is initialized on the 1st of June; Lim et al, 2007) and observation for Australian mean rainfall is 0.22, 0.56, 0.39 and 0.48, for summer, autumn, winter, and spring, respectively.

The fact that POAMA is able to predict tropical Indo-Pacific SST variability with good skill and Australian rainfall with moderate skill provides a good base for statistical-dynamical prediction because statistical post-processing itself cannot generate skill: the dynamical model must have skill in predicting some aspects of the climate.

3) Skill assessment of dynamical and statistical-dynamical forecast models

For statistical-dynamical prediction, we regressed the first five SVD mode time series of predicted SST from POAMA onto observed Australian rainfall for statistical bridging. For calibration, we regressed the first five SVD mode time series of predicted rainfall from POAMA onto observed rainfall. The resultant regression relationships were then used in forecast mode by plugging in the respective forecasts of SST or rainfall from POAMA. Because of the short period of hindcasts, we cross-validated the entire processes (leave out a year, develop the relationships, make a forecast for the left out year, and repeat using all years), including recalculation of the SVD modes each iteration.

We measured rainfall prediction skills of dynamical and statistical-dynamical models by hit rates of predicting below/above median rainfall over south eastern Australia (i.e. the percentage of correct forecasts for below/above median rainfall during 26 years in each season). Direct prediction from POAMA shows high skill in autumn and spring rainfall prediction over south eastern Australia but no skill in summer and winter. By contrast, statistical-dynamical schemes results in skilful predictions of south eastern Australia rainfall in summer and winter (Fig. 2). Statistical calibration increases hit rates of prediction of below/above median rainfall in all seasons except for spring, whereas statistical bridging works better in winter than the other two models. As a result, statistical post-processing results in local improvement of skill for the SEACI region. However, it might be achieved at the expense of skill in other areas (see Figure A-1 in Appendix for detailed geographical features of prediction skill).



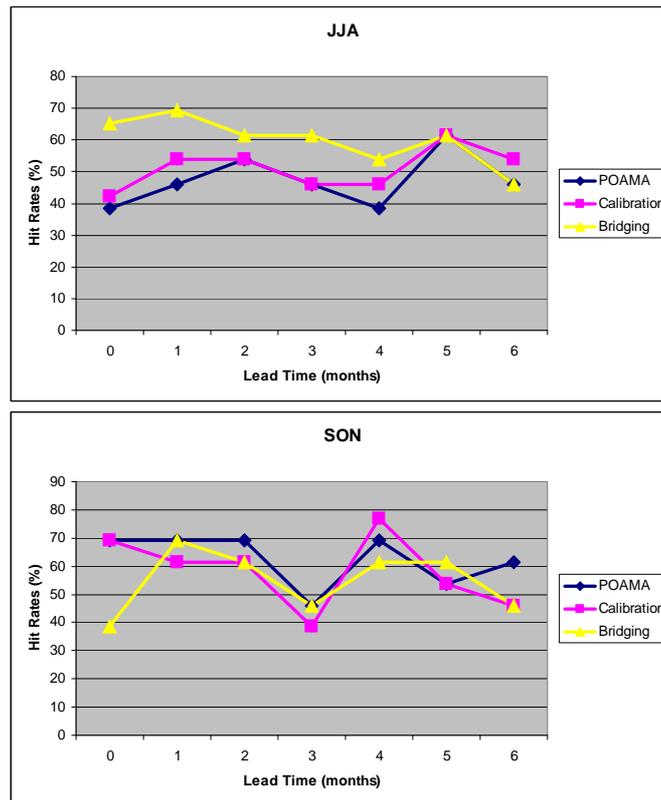


Figure 2: Hit rates (%) of predicting below/above median rainfall averaged over south eastern Australia (SEACI region, 38.5°-33.5°S, 137.5°-152.5°E).

Summary of methods and modifications (with reasons)

- Review literature and practises at other national centres
- Identify the predictable components of the climate system, such as sea surface temperatures (SSTs) in the Nino3 region (150° W to 90° W, 5° S to 5° N), with POAMA hindcasts that can be exploited to improve the prediction of climate variability in south-eastern Australia
- Investigate some simple statistical schemes that exploit the most predictable components of climate in POAMA (e.g., Nino3 SST)

Summary of links to other projects

This project has exploited findings from project 3.1.3 concerning the drivers of climate variability in SE Australia. The results here will feed into 3.1.4 and 3.2.2, where a more comprehensive analysis of climate predictions for SE Australia will be developed and evaluated.

Publications/reports arising from this project

Lim, E.-P. and H. H. Hendon 2007: Dynamical seasonal prediction of tropical Indo-Pacific SST and Australian cool season rainfall (in preparation)

Lim, E.-P. and H. H. Hendon 2007: Seasonal forecasts of Australian rainfall with statistical-dynamical methods (in preparation)

Hendon, H.H., E. Lim, O. Alves, and G. Wang, 2007: *Review of techniques to bridge/calibrate dynamical seasonal predictions with focus on south eastern Australia*. SEACI Technical Report, Milestone 3.2.2.

Lim, E., H.H. Hendon and O. Alves 2007: *Seasonal forecast of the tropical Indo-Pacific SST and Australian rainfall*. SEACI Technical Report, Milestone 3.2.2.

Acknowledgement

This research was supported by the South East Australian Climate Initiative

Recommendations for changes to work plan from your original table

None

References

Alves, O., G.Wang, A. Zhong, M. Smith, F. Tzeitkin, G. Warren, A. Schiller, S. Godfrey, and G. Meyers, 2003: POAMA: Bureau of Meteorology operational coupled model seasonal forecast system. *Science for drought - Proceedings of the National Drought Forum*. Queensland Government, Brisbane.

Bretherton, C. S., C. Smith., and J. M. Wallace, 1992: An intercomparison of methods for finding coupled patterns in climate data. *J. Climate*, **5**, 541–560.

Drosowsky, W. and L. Chambers, 2001: Near-global sea surface temperature anomalies as predictors of Australian seasonal rainfall. *J. Climate*, **14**, 1677–1687.

Feddersen, H., A. Navarra, and M. N. Ward, 1999: Reduction of model systematic error by statistical correction for dynamical seasonal predictions. *J. Climate*, **12**, 1974–1989.

Hendon, H.H., E. Lim, O. Alves, and G. Wang, 2007: *Review of techniques to bridge/calibrate dynamical seasonal predictions with focus on south eastern Australia*. SEACI Technical Report, Milestone 3.2.2.

Jones, D. A. and G. Weymouth, 1997: *An Australian monthly rainfall dataset*. Technical Report 70, Bureau of Meteorology.

Lim, E., H.H. Hendon and O. Alves 2007: *Seasonal forecast of the tropical Indo-Pacific SST and Australian rainfall*. SEACI Technical Report, Milestone 3.2.2.

McBride, J. L. and N. Nicholls, 1983: Seasonal relationships between Australian rainfall and the Southern Oscillation. *Mon. Wea. Rev.*, **111**, 1998–2004.

Nicholls, N., 1989: Sea surface temperatures and Australian winter rainfall. *J. Climate*, **2**, 965–973.

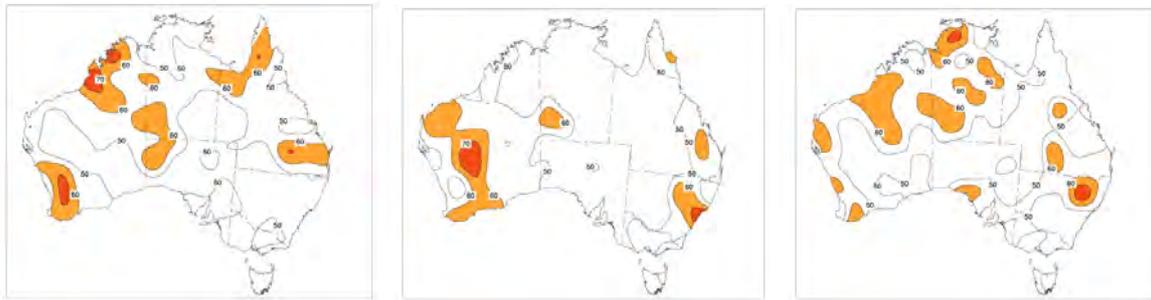
Wang, G., and H.H. Hendon, 2007: Sensitivity of Australian rainfall to inter-El Niño variations. *J. Climate*, **20**, 4211–4226.

Ward, M. N. and A. Navarra, 1997: Pattern analysis of SST-forced variability in ensemble GCM simulations: Examples over Europe and the tropical Pacific. *J. Climate*, **10**, 2210–2220.

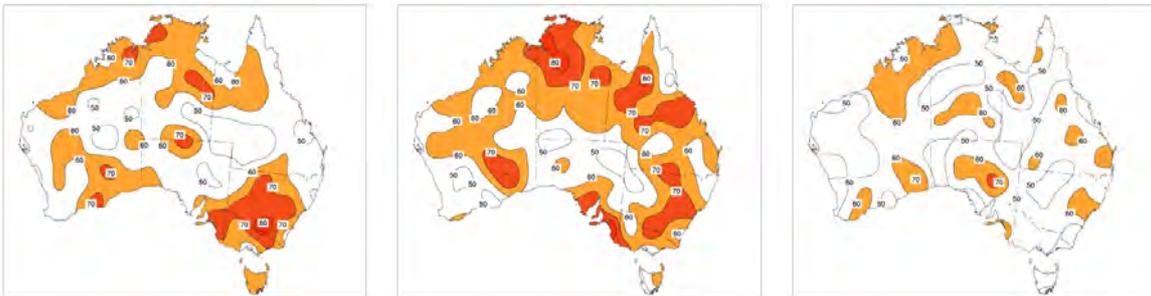
Project Milestone Reporting Table

To be completed prior to commencing the project				Completed at each Milestone date	
Milestone description ¹	Performance indicators ²	Completion date ³	Budget ⁴ for Milestone (\$)	Progress ⁵	Recommended changes to workplan ⁶
1. Review literature on statistical/dynamical prediction and investigate practises at other national centres	Report prepared	December 2006	25K	A technical report on literature review has been completed	None
2. Identify predictable modes of climate variability that can be used to bridge to rainfall and temperature in SE Australia in POAMA hindcasts	Report prepared (as part of Technical report for milestone 3)	March 2007	25K	Sensitivity of rainfall to inter-El Niño SST variations has been diagnosed (paper prepared). POAMA's ability to forecast inter-El Niño SST variations and SE Australian climate has been assessed.	None
3. Investigate some simple statistical schemes that exploit the most predictable components of climate with POAMA	BMRC Technical Report prepared	June 2007	11K	Trial combinations of predictors and predictands have been tested for statistical post-processing.	None

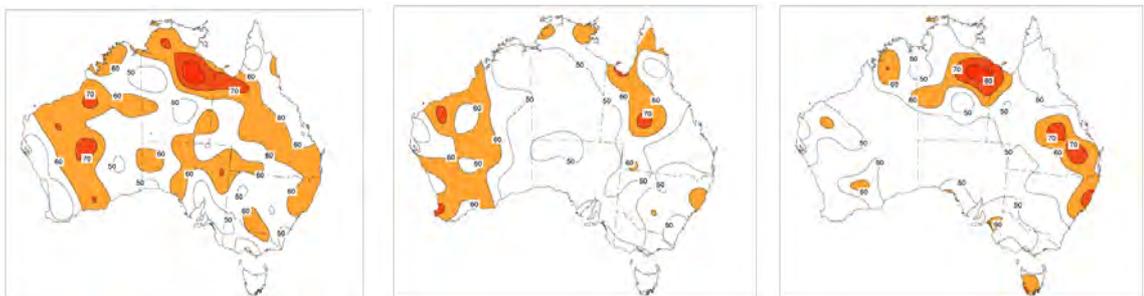
Appendix A



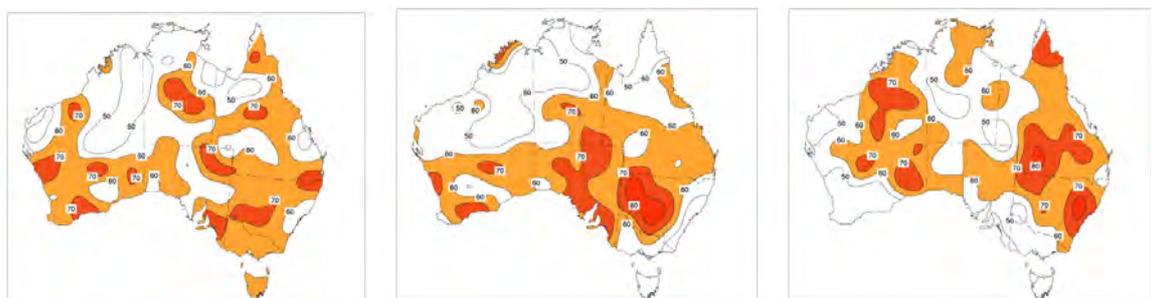
(a) DJF



(b) MAM



(c) JJA



(d) SON

Figure A-1: Hit rates (%) of below/above median rainfall prediction directly from POAMA (left panels), from a statistical calibration scheme (middle panels), and from a statistical bridging scheme (right panels) at lead time 0 month. The contour interval is 10%, and the hit rates greater than 60% are coloured.

Table A-1: Correlation of observed SST EOF time series with the corresponding POAMA SST EOF time series (their spatial domain is the same as shown in Figure 1). Bold numbers are the correlation coefficients statistically significant at the 95% confidence level. (i.e.- coefficients greater than 0.38 are regarded as being statistically significant, given 26 years of sample size).

(a) At lead time 0

correlation		EOF1	EOF2	EOF3	EOF4
DJF	POAMA	0.95	0.88	0.78	0.70
	Persistence	0.98	0.91	0.84	0.76
MAM	POAMA	0.91	0.92	0.81	0.69
	Persistence	0.90	0.90	0.88	0.42
JJA	POAMA	0.90	0.83	0.74	0.65
	Persistence	0.83	0.88	0.89	0.35
SON	POAMA	0.96	0.87	0.54	0.21
	Persistence	0.88	0.82	0.84	0.37

(b) At lead time 3 months

correlation		EOF1	EOF2	EOF3	EOF4
DJF	POAMA	0.88	0.66	0.67	0.50
	Persistence	0.78	0.58	0.62	0.16
MAM	POAMA	0.75	0.73	0.55	0.18
	Persistence	0.80	0.86	0.64	0.29
JJA	POAMA	0.67	0.80	0.54	0.54
	Persistence	0.44	0.69	0.59	0.02
SON	POAMA	0.73	0.76	0.44	0.19
	Persistence	0.40	0.58	0.75	0.06