Australian Government
Bureau of Meteorology

The Centre for Australian Weather and Climate Research
A partnership between CSIRO and the Bureau of Meteorology

CSIRO

Seasonal Forecast Verification in the Pacific using a coupled model POAMA and the statistical model SCOPIC

Andrew Cottrill, Andrew Charles, Kay Shelton, David Jones and Yuriy Kuleshov

CAWCR Technical Report No. 067

December 2013

www.cawcr.gov.au

Seasonal Forecast Verification in the Pacific using a coupled model POAMA and the statistical model SCOPIC

Andrew Cottrill[1], Andrew Charles[1], Kay Shelton[2], David Jones[1] and Yuriy Kuleshov[1]

[1]National Climate Centre (NCC), Bureau of Meteorology, Melbourne, Australia, 3008.
[2] Centre for Australian Weather and Climate Research (CAWCR), Bureau of Meteorology, Melbourne, Australia, 3008

CAWCR Technical Report No. 067

December 2013

ISSN: 1835-9884

National Library of Australia Cataloguing-in-Publication entry

Authors: Andrew Cottrill, Andrew Charles, Kay Shelton, Yuriy Kuleshov and David Jones

Title: Seasonal Forecast Verification in the Pacific using a coupled model POAMA and the statistical model SCOPIC.

ISBN: 978-1-4863-0237-6

Notes: Includes bibliographical references and index.

Subjects: Probability forecasts (Meteorology)--Pacific Area.
Meteorology--Pacific Area.
Weather forecasting--Pacific Area.
Pacific Area--Climate.

Dewey Number: 551.6330996

Enquiries should be addressed to:

Andrew Cottrill
National Climate Centre (NCC):
GPO Box 1289, Melbourne
Victoria 3001, Australia

a.cottrill@bom.gov.au

Copyright and Disclaimer

All images reproduced in grayscale. A colour version of CAWCR Technical Report No.067 is available online: http://www.cawcr.gov.au/publications/technicalreports.php

Contents

List of Figures

Appendix Figures

List of Tables

ABSTRACT

A verification study using the two seasonal forecast models developed by the Australian Bureau of Meteorology was completed over the Pacific region using rainfall from hindcast and real-time forecasts and observations from satellite and station data. The two forecast systems include the dynamical model POAMA (Predictive Ocean-Atmosphere Model for Australia) and the statistical model SCOPIC (Seasonal Climate Outlook for Pacific Island Countries). Skill scores using hit rates, linear error in probability space (LEPS) and the relative operating characteristic (ROC) are used at the regional and station level to assess model performance. Results show SCOPIC narrowly outperforms the dynamical model POAMA when hindcast forecasts are used. However, on equivalent time scales, POAMA has slightly higher skill than SCOPIC when using real-time forecasts, indicating both models still have important contributions to make to seasonal forecasting in the Pacific region.

1 INTRODUCTION

Seasonal forecasts in the Pacific region play an important role for mitigating impacts of climate extremes on Pacific nations and their economies. As part of the recently completed Pacific Adaptation Strategy and Assistance Program (PASAP; Charles et al. (2013b)) and the Pacific-Australia Climate Change Science and Adaptation Planning Program (PACCSAP; Kuleshov et al. (2012)), a verification study on rainfall from seasonal forecasts in the Pacific region was completed to monitor these projects and identify where improvements could be made. The two seasonal forecast systems involved in the two programmes are the dynamical model POAMA (Predictive Ocean-Atmosphere Model for Australia; Yin et al. (2011)) and the statistical model SCOPIC (Seasonal Climate Outlooks for Pacific Island Countries; Abawi et al. (2005a)), both developed by the Australian Bureau of Meteorology (BoM). The seasonal forecasts are currently provided online to the Pacific region via internet portals developed and maintained by the BoM. However, no formal assessment has yet been undertaken to measure the skill of the two forecast systems. Although several studies have recently looked at the forecast skill over the Pacific from hindcast and real-time forecasts (Wang et al. 2010; Barnston et al. 2012; Sooraj et al. 2012), they did not evaluate skill to the station level.

Pacific Island countries are susceptible to rainfall variability which is closely related to the phases of the El Niño–Southern Oscillation (ENSO) and El Niño and La Niña events (Schroeder et al. 2012). Locations close to the equator and east of about 180°E experience higher rainfall in El Niño years and lower rainfall in La Niña years. In contrast, many countries in the southwest Pacific experience the opposite rainfall changes, with lower rainfall in El Niño years and higher rainfall in La Niña years (Cottrill et al. 2013). These robust regional rainfall changes provide much of the skill in the statistical and dynamical seasonal forecasts over the tropical Pacific region (Barnston and Ropelewski 1992). El Niño and La Niña events also directly affect the rainfall activity and location of the South Pacific Convergence Zone (SPCZ) and the Inter-Tropical Convergence Zone (ITCZ), altering regional rainfall patterns (Brown et al. 2011; Vincent et al. 2011; Cottrill et al. 2013), indicating the prediction of rainfall associated with these convergence zones is very important for seasonal prediction and the Pacific nations (Charles et al. 2013a). As most El Niño and La Niña events tend to last 12 months or longer and usually reach a peak in December-January-February (DJF), this provides important prediction skill of rainfall at longer lead times for the southwest, west and central Pacific wet seasons.

Fifteen Pacific island countries were involved in the PACCSAP project (which ran from January 2012 to June 2013), and have been using the dynamical model POAMA, with ten of these countries also using the SCOPIC model for seasonal forecasting (Fig. 1) to improve their seasonal forecast capacity and reduce impacts from climate extremes.

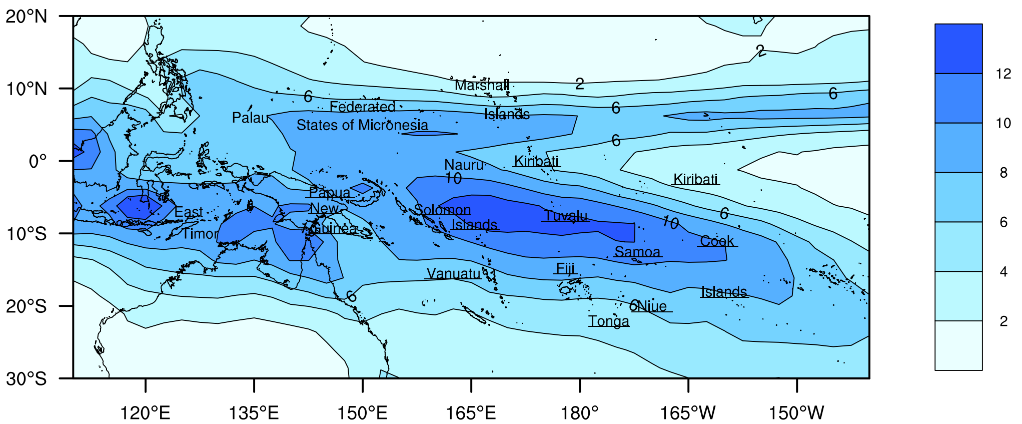

Fig. 1 Location of the 15 Pacific countries in the PACCSAP project and mean DJF rainfall (1982–2006) from CMAP (in mm day-1). The ten countries using the SCOPIC statistical model are underlined.

This study investigates the skill of the POAMA dynamical model in the Pacific region, as well as a comparison of the skill between POAMA and SCOPIC seasonal forecasts at the station level and is organised into the following sections. Section 2 describes the POAMA and SCOPIC forecast systems and discusses several previous studies. Section 3 describes data methods and verification techniques used in this study. Section 4 discusses the correlation of station rainfall and the 5VAR index across the Pacific region. Section 5 discusses the hindcast skill of POAMA, including the correlation of predicted ensemble mean rainfall with satellite observations, the regional skill of POAMA over the central, western and southwestern Pacific using tercile and above-median hit rates, with various lead times (LTs) and attribute diagrams. Section 6 compares a number of skill metrics from the POAMA and SCOPIC hindcast forecasts, including tercile hit rates and relative operating characteristic (ROC) scores at the station level. Section 7 describes the forecast skill from POAMA and SCOPIC using scored forecasts, tercile hit rates and linear error in probability space (LEPS) scores from the station level from real-time forecasts. Section 8 provides a discussion of the results for improving seasonal forecasts and the future directions of the two seasonal predictions systems at the BoM.

2 POAMA AND SCOPIC MODELS

2.1 Dynamical model POAMA

The dynamical model POAMA is a coupled ocean-atmosphere climate model used for seasonal and intra-seasonal forecasts in Australia (Lim et al. 2010b; Hudson et al. 2011; Hudson et al. 2013) and more recently for seasonal forecasts in the Pacific region (Cottrill et al. 2013). POAMA uses the BoM Research Centre Atmospheric Model version 3.0 (BAM3.0) for the atmosphere (Colman et al. 2005) and the Australian Community Ocean Model version 2 (ACOM2), based on the Geophysical Fluid Dynamics (GFDL) Modular Ocean Model version 2 (MOM2; Schiller et al. (2002)) for the ocean. The first version of POAMA was the single model version POAMA-1 released in 2002, subsequently upgraded to POAMA1.5b in 2007, and the multi-model version POAMA2.4 in 2011. POAMA-2 has an improved ocean data assimilation scheme (Yin et al. 2011), which improves forecast reliability compared to earlier versions (Langford and Hendon 2013).

The atmospheric model BAM3.0 is a spectral transform model using a grid spacing of 2.5° x 2.5° (72 x 144 grid points), with 17 vertical levels (Colman et al. 2005). It is initialised with the atmosphere and land initialisation scheme (ALI) which generates realistic initial conditions of the land and atmosphere. The ocean model ACOM2 has a variable grid spacing with the highest resolution at the equator (2° in zonal direction and 0.5° in meridional direction), which improves ocean dynamics and ENSO behaviour. There are 25 levels in the ocean, with 12 levels above 185 m. The new advanced ocean initialisation scheme provided by the POAMA Ensemble Ocean Data Assimilation Scheme (PEODAS), assimilates ocean temperature and salinity into the model every three days and generates an ensemble of initial states by adjusting the wind and surface fluxes (Yin et al. 2011). Further details on the physics of the POAMA model can be found in Schiller et al. (2002), Colman et al.(2005) and Yin et al. (2011).

POAMA has been used for seasonal forecasts in Australia since October 2002 (Wang et al. 2008b), and was introduced into the Pacific region from 2011 under the PASAP project. POAMA simulates many aspects of tropical Pacific climate, including aspects of the Madden Julian Oscillation (Zhang et al. 2006) and the major rainfall changes in the SPCZ and ITCZ during El Niño years and La Niña years (Vincent et al. 2011; Charles et al. 2013a; Cottrill et al. 2013). Since much of the forecast skill lies in the tropical equatorial ocean associated with ENSO (Barnston and Ropelewski 1992), skill is higher over the Pacific region, contiguous with the tropical Pacific. The highest rainfall skill occurs along the equator east of about Papua New Guinea in all seasons and is strongest in the austral summer when rainfall is highest (Cottrill et al. 2013). However, high skill also occurs in parts of the southwest Pacific in DJF in a broad zone from the Solomon Islands to Vanuatu, eastwards towards Fiji and Tonga associated with the SPCZ.

The PASAP portal where seasonal forecasts based on POAMA are issued for the National Meteorological Services (NMS) in the Pacific can be found at

http://poama.bom.gov.au/experimental/pasap/.

In this study, we use version POAMA2.4 (P2.4) for the analysis and is called 'POAMA' hereafter.

2.2 Statistical model SCOPIC

The statistical model SCOPIC has been used for nearly a decade in the Pacific region via the Pacific Island Climate Prediction Project (PI-CPP), to assist the Pacific NMS to produce seasonal forecasts from meteorological data for local communities. The statistical model is based on linear discriminant analysis (LDA), which uses historical data as analogues to predict rainfall (either as terciles or above/below median). Up-to-date monthly rainfall (predictands) from each station and the monthly indices of the Southern Oscillation Index (SOI) or sea surface temperature anomaly (SSTa) empirical orthogonal functions (EOFs; predictors) are used to forecast rainfall. Monthly values of the SOI start in January 1876 and for the SSTa EOFs (using SST1 and 9; (Drosdowsky and Chambers 2001)) in January 1949. Some stations have over 100 years of high quality rainfall data available to train the model, such as Port Moresby (Papua New Guinea) and Apia (Samoa), where monthly rainfall records extend back to around 1890. However, depending on which predictor is selected, not all of the rainfall data is used. The selection of the predictors used by each country and the number of months for the forecast was determined by individual NMS at various workshops and training activities (Abawi et al. 2005a; Abawi et al. 2005b).

SCOPIC is part of the BoM's COSPPac program designed to build seasonal prediction capacity in the Pacific NMS, with the continued development of the new ocean and climate services products available at: http://reg.bom.gov.au/cosppac/comp/. We use version 3.0 of SCOPIC for this analysis.

2.3 POAMA and SCOPIC real-time forecasts

The main steps involved in the production of real-time seasonal forecasts for the Pacific region from SCOPIC and POAMA are illustrated as a simplified flow diagram (Fig. 2). Monthly values from the SOI and SST1 and 9, as well as the monthly rainfall from each station are used by SCOPIC for the LDA. Thresholds for the terciles and above-median probabilities are generated for the seasonal forecasts up to nine months ahead (LT=7 months), and can be produced locally on desktop/laptop. In POAMA, a supercomputer uses initial conditions from the ocean and atmosphere to assimilate data into the coupled global climate model (GCM) from many sources, using the PEODAS scheme, generating 30 ensembles. The dynamic model is run for 9 months. Gridded forecasts of rainfall are produced (total, anomaly and lower and upper terciles), with the nearest grid point to each station location used to generate the station seasonal forecast. A description of the software architecture of both systems can be found in Charles et al. (2011). Forecasts from both POAMA and SCOPIC are issued using a LT of one month (LT=1; see section 3.4 for further details).

The POAMA and SCOPIC forecasts are being used by ten countries in the southwest Pacific and equatorial region, with a further five countries using POAMA in the west and northwest Pacific (the Federated States of Micronesia, Nauru, Palau and the Marshall Islands) and the Indonesian region (East Timor).

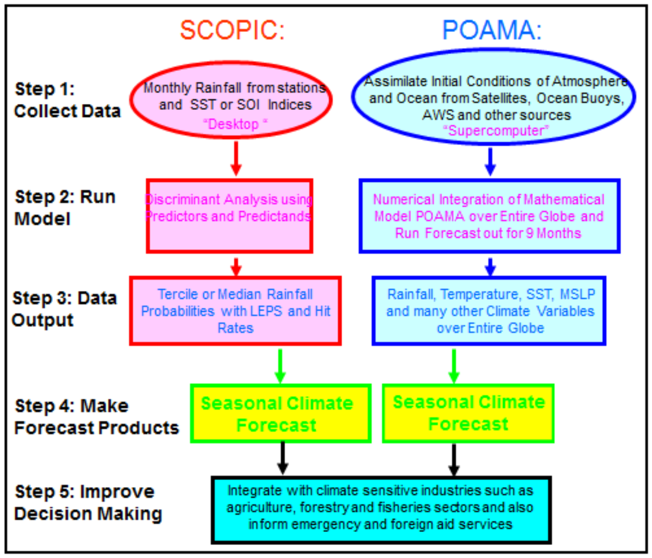

Fig. 2 Simplified flow diagram showing the main steps to produce a real-time seasonal forecast from the SCOPIC and POAMA models.

3 DATA METHODS AND VERIFICATION

3.1 Station selection and rainfall data

Monthly rainfall from 14 stations across the Pacific region is used for the verification of the seasonal forecasts from POAMA and SCOPIC for the hindcast forecasts. These stations are: Tarawa (Kiribati) and Funafuti (Tuvalu) in the equatorial Pacific; Nadi Airport, Rarawai, Nabouwalu, Suva and Rotuma from Fiji, Nuku'alofa (Tonga), Alofi (Niue), Apia (Samoa), Rarotonga (Cook islands) and Honiara (Solomon Islands) from the SPCZ and Port Vila (Vanuatu) and Port Moresby (Papua New Guinea) from the southwest Pacific region. For real-time forecasts, 13 stations are used for verification. This includes the 11 hindcast stations (excluding Nabouwalu, Rarawai and Suva), plus Faleolo (Samoa) and Wewak (Papua New Guinea). Forecasts are verified for the four seasons - austral summer (December-January-February; DJF), autumn (March-April-May; MAM), winter (June-July-August; JJA) and spring (September-October-November; SON) and all seasons for real-time forecasts.

Verification of the gridded monthly rainfall from POAMA in the hindcast forecasts is completed using the CPC Merged Analysis for Precipitation (CMAP; Xie and Arkin (1997)). The CMAP analysis contains a blend of gauge observations and satellite data and is produced by the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP-NCAR) reanalysis. The monthly rainfall used in the hindcast forecasts is verified for 1980–2006 or 1982–2006. Rainfall forecasts from POAMA have been calibrated using the inflation of variance (IOV) method after Johnson and Bowler (2009) and are cross-validated. Further information on the IOV technique used here can be found in Cottrill et al. (2013).

3.2 Correlation of station rainfall to 5VAR

Station rainfall was correlated with the 5VAR index for the period 1950–2011. The 5VAR index is an index formed by combining the mean sea level pressure from Tahiti and Darwin and the three Niño indices (Niño3, Niño3.4 and Niño4) representing the equatorial SST (Kuleshov et al. 2008). Results highlight the ENSO relationship across the Pacific region during the four austral seasons. Stations are divided into three groups representing the equatorial, the SPCZ and the southwest Pacific regions. Since much of the skill from the POAMA and SCOPIC models is derived from the tropical Pacific and associated with ENSO, the correlation indicates when forecasts are more likely to have higher or lower skill at certain times of the year and show how the rainfall patterns vary across the three regions.

3.3 POAMA hindcast skill over the tropical Pacific region

Several studies have looked at the hindcast skill of POAMA and several international GCMs over the Australian region assessing rainfall and skill scores, such as above-median hit rates for various seasons and LTs (Lim et al. 2010a; Langford and Hendon 2011). They show that the highest skill in the Australian region at longer LTs is attained in the austral spring.

This study uses the hindcast forecasts from POAMA over the western and central tropical Pacific Ocean between 110°E to 140°W and 20°N to 30°S, which also includes northern Australia, similar to Cottrill et al. (2013). The hindcast forecasts span the time period 1980–2006, and run for nine months each, which equates to a LT=6 months for seasonal three month average forecasts. All results are cross validated. We show the correlation of predicted ensemble mean rainfall from POAMA and CMAP, as well as the tercile and above-median hit rates plus attribute diagrams. We use the four austral seasons MAM, JJA, SON and DJF and LTs 0, 1, 2, 3, 4 and 6 months.

For tercile forecasts, a hit rate of 33.3% represents climatology. We define the skill of tercile hit rates as being very high (>80%), high (60–80%), moderate (40–60%) and no skill (<30%). The tercile hit rates are the combined hit rates from each of the lower, middle and upper terciles. For the above-median hit rates, a value of 50% represents climatology, with values considered very high skill (>80%), high skill (70–80%), moderate skill (60–70%) and no skill (<50%). To summarise the tercile and above-median hit rate, an average hit rate is calculated for each of the twelve seasons and the above mentioned six LTs to construct line plots to show the seasons and LTs with higher or lower skill.

3.4 Station hindcast skill from POAMA and SCOPIC

The selection of skill scores for forecast verification can be challenging due to the large range of skill scores now available and the many types of forecasts which can be verified (Jolliffe and Stephenson 2003; Jolliffe and Stephenson 2012). In this study, rainfall from SCOPIC and POAMA in seasonal forecasts is probabilistic and analysed as categorical forecasts. We have selected tercile hit rates (also known as 'percent consistent' in SCOPIC) to assess the accuracy of seasonal forecasts and ROC scores to measure the discrimination between the tercile categories.

All seasonal forecasts from POAMA and SCOPIC models are cross-validated in the hindcast forecasts.

The hit rates are defined as the ratio of correct forecasts to the total number of occurrences (Wilks 2006) and is also known as the probability of detection (POD). A contingency table showing the three category or tercile forecasts can be found in Cottrill et al. (2012). The ROC score is the ratio between the hit rate and the false alarm rate (Wilks 2006). The false alarm rate is the ratio of false alarms to non-occurrences. A plot of the hit rate versus the false alarm rate shows the area under the forecast curve as the ROC score. A ROC score of 0.50 or above indicates a positive skill in the forecast, whilst a value of below 0.50 represents no skill.

Station hindcast forecasts are used for skill assessment using one time period from POAMA (1982–2006) and two time periods from SCOPIC (1982–2006 and 'All Years'). The term 'All Years' in relation to SCOPIC refers to using all the available rainfall data and predictors from each station to make the forecast. This may vary from 55 years at Honiara to 123 years at Apia. Seasonal forecasts from POAMA and SCOPIC are used to calculate the skill scores using a LT=1 for the four austral seasons. This means for example, the POAMA forecasts initialised on the 1st of November are used to make a forecast for DJF. In the Pacific region, the NMS generate their real-time seasonal forecasts from SCOPIC for each station using the latest monthly SST1 and 9 or SOI information and all the hindcast years. Monthly values from the SST1 and 9 start in 1949, and for the SOI in 1890. In this study, we use the two periods 1980–2006 and 'All Years' from SCOPIC to show the change in skill between 27 and 'All Years' of data. Seven stations use the SOI as the predictor (using an average of 91 years of data) and seven stations use the SST1 and 9 as the predictor (using an average of 62 years of data), which equates to 77 years for 'All Years' and all 14 stations in SCOPIC. A summary of station data used in SCOPIC is shown in Table 1. The number of years may vary depending on missing data.

We also show that the method by which station level forecasts are produced from POAMA's coarse gridded output can affect the skill of the forecasts. Two methods are compared: the nearest grid point versus bilinear interpolation (distance weighted averaging of the four nearest points) to the station location. Tercile ROC scores are shown to demonstrate the differences between the two methods.

To see if SCOPIC performs significantly better when the ENSO signal is strong, the hindcast data was divided (stratified) into three groups representing El Niño, La Niña and neutral years for the period 1950–2011 (62 years). By separating the predictors and predictants into the three groups, it was envisaged that higher skill would be attained. Tercile hit rates, LEPS percentage scores and tercile ROC scores are used to show the changes in skill scores for the 14 stations and the four austral seasons DJF, MAM, JJA and SON.

Table 1 Summary of the 14 Pacific stations showing the time period and number of years of available observations and the type of predictor used in SCOPIC. All stations use three month average values for the predictors, except Honiara, which uses only one month.

Station Name and Region	Island Group	Period of Observations	Number of Years*	Predictor
Equatorial Region				
1.Betio (Tarawa)	Kiribati	1949–2012	61-64	SST1 and 9
2. Funafuti	Tuvalu	1933–2012	79-80	SOI
SPCZ Region				
3. Nadi Airport	Fiji	1942–2012	69-71	SOI
4. Rarawai	Fiji	1910–2007	96-98	SOI
5. Nabouwalu	Fiji	1918–2012	92-95	SOI
6. Suva	Fiji	1942–2012	70-71	SOI
7. Rotuma	Fiji	1912–2012	97-99	SOI
8. Nuku'alofa	Tonga	1949–2012	62-64	SST1 and 9
9. Alofi	Niue	1950–2012	62-63	SST1 and 9
10. Apia	Samoa	1890–2012	122-123	SOI
11. Rarotonga	Cook Is	1949–2012	62-64	SST1 and 9
12. Honiara	Solomon Is	1954–2012	55-58	SST1 and 9
Southwest Pacific Region				
13. Port Vila	Vanuatu	1953–2012	59-60	SST1 and 9
14. Port Moresby	Papua New Guinea	1949–2012	52-63	SST1 and 9

Note: Asterisk indicates minimum and maximum number of years in a season.

3.5 Real-time station forecasts from POAMA and SCOPIC

Real-time seasonal forecasts from SCOPIC have been routinely issued by the Pacific NMS (for up to 57 stations across ten Pacific countries) since mid-2007. Seasonal forecasts from POAMA have been issued via the PASAP portal for several stations (initially 22 and now 44) to the Pacific NMS since December 2011. Here, we analyse the seasonal forecasts from January 2012 through to October 2013 from thirteen stations using a LT=1 and 221 forecasts (20 seasons). We use scored forecasts, tercile hit rates and LEPS scores for verification, averaged for all stations. Scored forecasts are defined by comparing the forecast rainfall tercile probabilities with corresponding observations. For the scored forecasts, seasonal forecasts are verified as either consistent (value = +1.5), near consistent (+0.5) or inconsistent (0), with these values (+1.5, +0.5 or 0) summed for all stations and divided by the perfect total (i.e. all consistent forecasts of 1.5), to represent an average scored forecast in percentage terms. A score of 100% would mean all forecasts were correct, whilst a 0% score would mean all forecasts were inconsistent and missed the correct tercile by 2 categories. LEPS scores show the skill of forecasts compared to climatology, penalising bad forecasts and rewarding good forecasts. LEPS scores are calculated using the revised LEPS methodology described in Potts el al. (1996). Forecasts with a value above zero indicate a good forecast, whilst values below zero indicate a poor forecast.

4 CORRELATION OF STATION RAINFALL TO THE 5VAR INDEX (1950–2011)

The correlation of station rainfall with the 5VAR index is shown for the 14 Pacific stations across the Pacific region.

4.1 Results

To highlight the strong connection between rainfall at the 14 Pacific stations in the Pacific region and ENSO, we show the correlation of station rainfall with the 5VAR index for the four austral seasons and the period 1950–2011 (Table 2). As mentioned previously, the 5VAR index is an index formed by combining the mean sea level pressure from Tahiti and Darwin and the three Niño indices (Niño3, Niño3.4 and Niño4). The correlation between the 5VAR and Niño3.4 index for the period 1950–2011 is extremely high, with correlation values of +0.98, +0.97, +0.97 and +0.98 for DJF, MAM, JJA and SON respectively. Hence, the differences in the correlation values between station rainfall with the 5VAR or the Niño3.4 index (not shown) are generally small (≤0.05).

Table 2 Correlation of station rainfall and the 5VAR index from 14 Pacific stations for the four austral seasons and the period 1950–2011. Statistically significant correlation values at the 5% level (α=0.025 and r≥0.25 by two tailed Student-t test with 62 samples) are boldfaced.

Station Name and Region	Island Group	DJF	MAM	JJA	SON
Equatorial Region					
1.Betio (Tarawa)	Kiribati	**0.72**	**0.68**	**0.84**	**0.79**
2. Funafuti	Tuvalu	0.16	**0.39**	**0.32**	**0.27**
SPCZ Region					
3. Nadi Airport	Fiji	**-0.70**	**-0.61**	0.00	**-0.60**
4. Rarawai	Fiji	**-0.63**	**-0.66**	-0.03	**-0.64**
5. Nabouwalu	Fiji	**-0.56**	**-0.41**	-0.24	**-0.62**
6. Suva	Fiji	-0.14	-0.19	-0.18	**-0.38**
7. Rotuma	Fiji	**-0.46**	0.16	0.19	0.08
8. Nuku'alofa	Tonga	**-0.66**	**-0.34**	0.11	**-0.42**
9. Alofi	Niue	**-0.60**	**-0.38**	-0.06	**-0.46**
10. Apia	Samoa	**-0.49**	**-0.25**	**-0.25**	**-0.35**
11. Rarotonga	Cook Is	**-0.46**	**-0.41**	-0.20	-0.23
12. Honiara	Solomon Is	**-0.56**	**-0.32**	0.21	-0.23
Southwest Pacific Region					
13. Port Vila	Vanuatu	**-0.49**	**-0.33**	**-0.36**	**-0.55**
14. Port Moresby	Papua New Guinea	**-0.25**	-0.21	-0.03	**-0.46**

In the equatorial region at Tarawa (Kiribati), the correlations are positive and high (>0.60) for the four seasons, with the highest value in JJA (+0.84). At Funafuti (Tuvalu), the correlation values are also positive but much weaker (<0.40). The lowest correlation among the equatorial locations occurs in DJF (+0.16), and this is much lower than the correlation of +0.51 reported in Cottrill et al. (2012) for the period 1982–2006 using the Niño3.4 index, indicating rainfall in this region is dependent on decadal ENSO variability. A positive (negative) correlation indicates higher (lower) rainfall in El Niño (La Niňa) years when tropical convection is enhanced (suppressed).

In the SPCZ and southwest Pacific regions, the correlation values are mostly negative, similar to Cottrill et al. (2012) who used the Niño3.4 index. In DJF, when rainfall is highest over the SPCZ and the southwest Pacific region (Fig. 1), the correlations are generally highest, with ten stations having moderate (0.40–0.60) or strong (>0.60) negative correlation values to the 5VAR index. Strong negative correlation values occur at Nadi Airport (-0.70), Rarawai (-0.63), Nuku'alofa (-0.66) and Alofi (-0.60). The weakest correlations are at Suva (-0.14) and Port Moresby (-0.25). In SON and MAM, moderate to strong negative correlations occur at seven and four stations respectively, with the highest correlation values at Rarawai (-0.64 and -0.66 respectively). In JJA, the correlations are generally the weakest, with no station having a correlation value above r=0.40. Only two stations (Apia: r=-0.25 and Port Vila: r=-0.36) have weak negative correlations (-0.20–0.40) which are statistically significant ($r \geq 0.25$). This indicates that rainfall variability across the SPCZ and the southwest Pacific region is not closely related to ENSO during JJA, when rainfall is generally low. Suva and Rotuma have very weak correlations (<0.20) in three seasons, indicating that seasonal forecasting at these locations will be challenging for most of the year.

Although similar correlations were described between rainfall and the Niňo3.4 index in Cottrill et al. (2012) and summarised by Cottrill et al. (2013) for LT=0, this analysis shows that the moderate to strong correlations persist at LT=1. This provides more confidence to the seasonal forecasts, even though major changes in the frequency, intensity or types of El Niño or La Niña events, affect the rainfall variability in the tropical Pacific (Mendelssohn et al. 2005; Lee and McPhaden 2010; Ramesh and Murtugudde 2013).

5 POAMA HINDCAST SKILL OVER THE TROPICAL PACIFIC REGION

We now discuss the correlations of monthly rainfall between POAMA and CMAP, the tercile and above-median hit rates and the reliability of forecasts to assess the regional skill of the dynamical model in the Pacific region.

5.1 Correlation of POAMA rainfall and CMAP

To assess the skill of POAMA over the central and western tropical Pacific, the correlation between mean ensemble rainfall and CMAP is shown for the four austral seasons from 1982–2006 and a LT=1 month (Fig. 3). We use the period 1982–2006, so a direct comparison can be made of the correlation values shown in Fig. 6 (Cottrill et al. 2013) using a LT=0. High correlations ($r \geq 0.70$) are attained over most of the equatorial Pacific in all seasons, and most seasons over the Maritime continent east of Borneo and west of Papua New Guinea (except in

MAM) and the Philippines region (except JJA). In the southwest Pacific, the highest correlation is in DJF (the wet season), with moderate values (r≥0.50) in SON and MAM, and the lowest correlation in JJA. As noted by Cottrill et al.(2013), a region of no skill (r<0.30) occurs over most of PNG and in the Bismarck Sea in all seasons. A band of no skill extends from the Solomon Islands east-southeast towards Samoa in DJF, MAM and SON. This coincides with the axis of maximum rainfall associated with the SPCZ (Fig. 1), but represents the region between the SPCZ and ITCZ in POAMA, indicating the SPCZ is located further south and west in the model than indicated from observations. The low or no skill in DJF is due to the negative rainfall anomalies in La Niña years being simulated too far south from the ITCZ at ~180° (regions with positive rainfall anomalies). In contrast, positive rainfall anomalies in El Niño years are simulated too far west into the PNG region, instead of negative rainfall anomalies (not shown). In JJA, the band of low or no skill lies further south and extends from the Coral Sea towards Fiji and the Cook Islands.

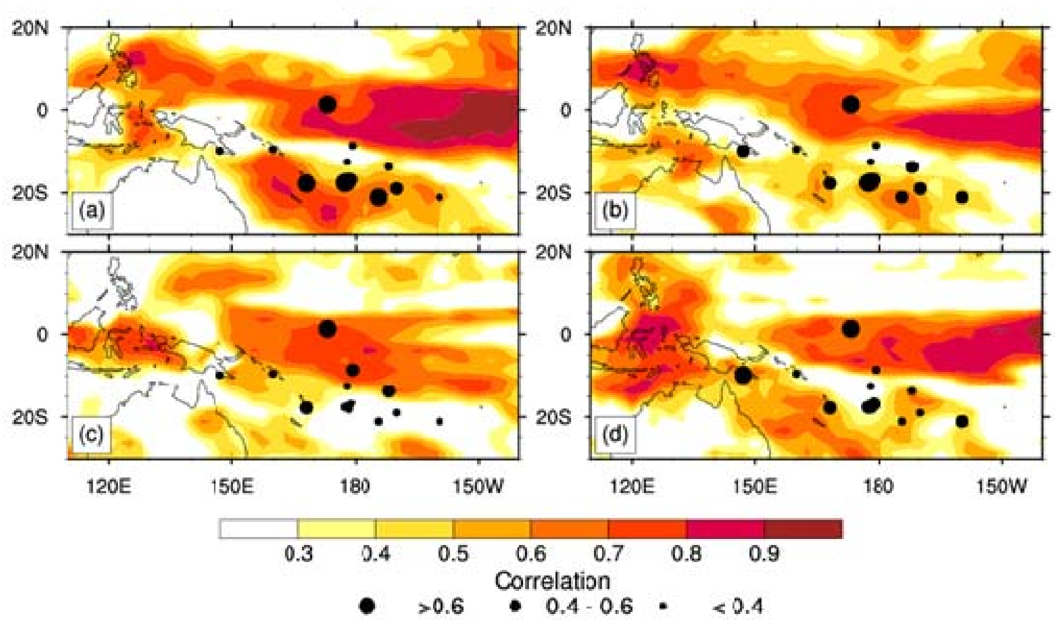

Fig. 3 Maps of the correlation between predicted ensemble mean rainfall from POAMA (LT=1) and CMAP for the period 1982–2006 for (a) DJF, (b), MAM, (c) JJA and (d) SON. Statistically significant correlation at the 90% confidence level is 0.30. Black dots are the correlation values at the 14 Pacific stations.

Also shown in Fig. 3 is the correlation of predicted ensemble mean rainfall at the 14 station locations. This indicates Kiribati is located in a region of high skill all year round, whilst high skill is achieved in parts of the southwest Pacific including Vanuatu, Fiji and Tonga in DJF. Countries with generally low skill include Tuvalu, northern Fiji (Rotuma) and parts of PNG. The change in skill at the station level between LT=0 and LT=1 is generally small for DJF and JJA and slightly lower for SON, whereas MAM shows an increase in skill across all stations.

5.2 Tercile hit rates

The tercile hit rates of gridded rainfall rainfall for the Pacific region for the four austral seasons and six LTs are shown in the panel plots in Fig. 4 for the period 1980–2006 over the region 110°E to 140°W and 20°N to 30°S (and all seasons in Appendix 1). The highest tercile hit rates (>80%) are located along the equatorial Pacific region in DJF and JJA, with slightly lower hit rates in MAM and SON for a LT=0. The region of very high skill (>80%) over the equatorial Pacific, only persists in DJF with increasing LTs to four months. This region is up to ~1800 km wide extending from 7.5°N to 7.5°S and from ~170°W to 155°W, forming a typical 'horseshoe' zone (apex at ~180°E) and represent the two converging zones of the SPCZ and the ITCZ. This region covers much of the Kiribati group (from Tarawa in the west to the Line Islands in the east). Very high skill also occurs in JJA (LT=0) over the Kiribati region near Tarawa and just north of Samoa.

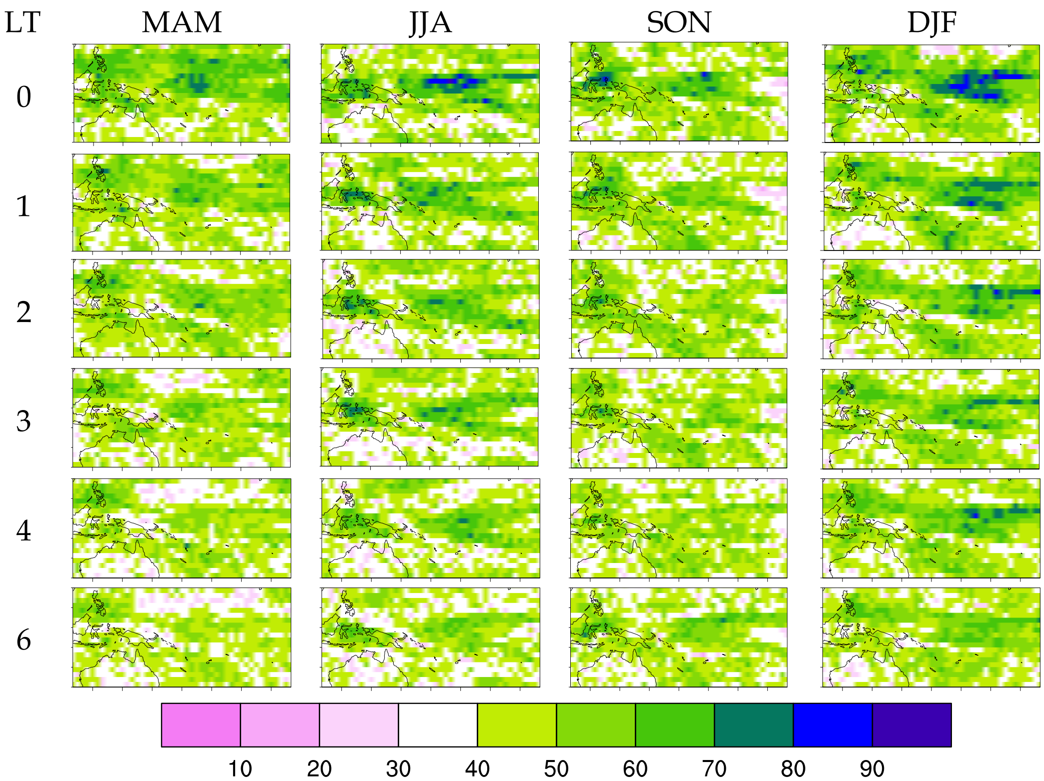

Fig. 4 Tercile hit rates for the tropical Pacific region for the four austral seasons and six LTs using POAMA for the period 1980–2006. Hit rates in shades of green and blue (>40%) are considered skilful, whereas pink shades (<30%) have no skill.

In DJF, in the southwest Pacific there is a large region of moderate to high skill (>40–80%) over the southern Solomon Islands, Fiji, Samoa, Niue, Tonga, Vanuatu and much of the Coral Sea. Over the northwest Pacific, there is moderate to high skill over the Marshall Islands, Federated States of Micronesia and the Palau region. An area of lower skill (<40%) occurs over parts of northeast Papua New Guinea, the region west of Tahiti and over parts of central Australia. Since DJF is the wet season in the southwest Pacific region, the high skill in this region is extremely valuable for providing accurate forecasts for agriculture and other climate sensitive industries.

Although the forecast skill is generally lower in MAM, JJA and SON than in DJF, high skill (60–80%) is achieved along the equator and north of Fiji at LT=0. With increasing LTs, the tercile hit rates fall slowly, but still remain skilful (>40%) at longer LTs (3, 4 and 6 months) over large areas of the equatorial Pacific, the southwest Pacific, the Maritime continent and in the Philippines region. In SON, there is a region of no skill (<30%) east of ~160°W along the equator and also in ASO (see Appendix 1) with short LTs of 1, 2 and 3 months, but this improves to near climatology (white) at LTs of 4 and 6 months.

5.3 Above-median hit rates

The above-median hit rates of rainfall for the Pacific region for the four austral seasons and six LTs are shown in Fig. 5 for the period 1980–2006 (and all seasons in Appendix 2). The highest hit rates (>80%) are located along the equatorial Pacific region (similar to Fig. 4) and are highest in DJF, followed by SON, MAM and JJA. This region of very high skill is similar to the pattern shown in Fig. 4, except the very high skill persists for longer LTs using the above-median hit rates. In DJF, the zone of very high skill in the equatorial Pacific region persists for LTs up to 4 months, before decreasing in size from LT=4 to 6 months. In JJA, very high skill decreases with increasing LT, but still forms a zone of higher skill over the equatorial Pacific region at LT=6 months. In SON, the very high skill decreases rapidly from LT=1 to LT=2 than in JJA or DJF, but then surprisingly improves at LT=4 and 6 months to be comparable to the hit rates at LT=1 and 2 months. In MAM, the very high skill over the central equatorial Pacific generally decreases faster than the other seasons as LT increases, and does not recover and is almost completely gone after LT=4 months.

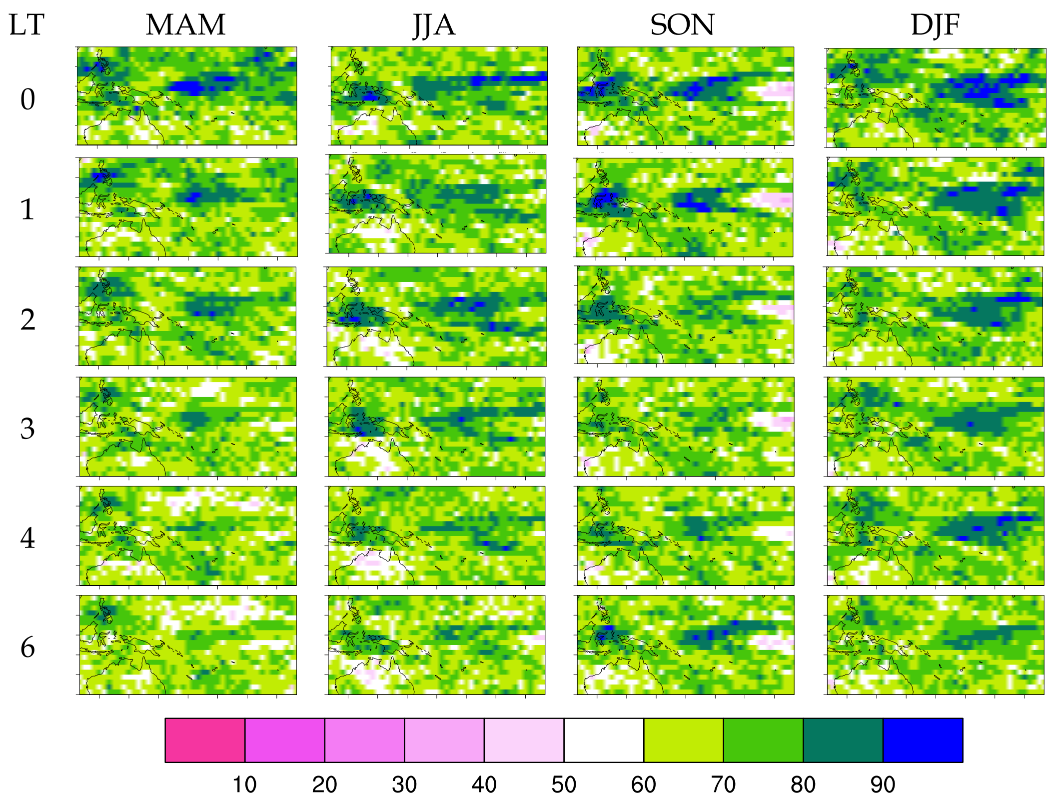

Fig. 5 Above-median hit rates for the tropical Pacific region for the four austral seasons and six LTs using POAMA for the period 1980–2006. Hit rates in shades of green and blue (>60%) are considered skilful and below 50% no skill.

In DJF in the southwest Pacific, high skill (≥70%) extends from the Solomon Islands and southeast of Papua New Guinea towards Vanuatu and New Caledonia, and then eastwards to Fiji, Tonga and the Cook Islands. This region of higher skill is similar to that shown in Fig. 4. This area of high skill persists to a LT=4 months. In the other seasons, although the skill is weaker over the southwest Pacific, moderate skill (>60%) continues up to a LT=6 months. Over the Maritime continent and the Philippines region, the high or very high skill patterns are similar to the tercile hit rates, with high or very high skill over the Maritime continent in JJA and SON and the Philippines region in DJF and MAM for all LTs. This indicates seasonal forecasts from POAMA would be of valuable assistance to Indonesia and the Philippines region, and could provide tangible economic benefits at a relatively low cost.

5.4 Line plots of average tercile and above-median hit rates

To summarise the spatial hit rates from POAMA (sections 5.2 and 5.3), line plots showing the area averaged tercile and above-median hit rates over the Pacific region are shown in Fig. 6a and 6b respectively (20°N–30°S and 110°E–140°W, 12 seasons, six LTs and the period 1980–2006).

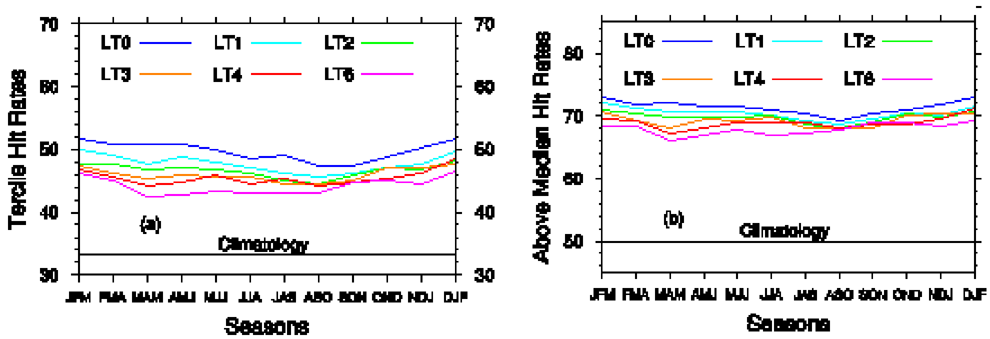

Fig. 6 Area averaged (a) tercile hit rates and (b) above-median hit rates over the Pacific region for the 12 seasons (JFM to DJF) and six LTs from POAMA for the period 1980–2006. Hit rates above the black horizontal climatology line (33.3% for terciles and 50.0% for above-median) indicate positive skill.

Figure 6a shows that the area averaged tercile hit rates are highest in the austral summer (DJF and JFM) for all LTs compared to the other seasons, which is important since this represents the wet season for the equatorial and southwest Pacific region when flooding or major droughts can occur. Hit rates of ~52% in DJF and JFM decrease to ~46% at a LT=6 months. In contrast, the hit rates are generally lowest at the end of austral winter and early spring (ASO and SON), with hit rates of ~47% falling to ~45% with increasing LTs. Austral autumn (MAM, AMJ and MJJ) shows the greatest decrease in the hit rate from ~51% at LT=0 to ~42% at LT=6 months. This period is when El Niño and La Niña events begin to develop, and is generally the most difficult time of year to produce a skilful forecast (Barnston et al. 2012).

Figure 6b shows the area averaged above-median hit rates, which shows the seasonal cycle is quite similar to the tercile hit rates, with the highest hit rates from LT=0 occurring in the austral summer (DJF and JFM with ~73%), and the lowest hit rates in late austral winter and early spring (ASO with ~69%). However, the above-median hit rates fall more slowly with increasing LTs compared to the tercile hit rates, falling from an average value of 71% at LT=0, to 68% at LT=6 months (a fall of 3%). This compares to a fall of ~6% for the tercile hit rates.

5.5 Reliability and resolution of POAMA forecasts

To assess the reliability and resolution of seasonal forecasts from POAMA, attribute diagrams are made for the four austral seasons and six LTs over the Pacific region (110°E–140°W and 20°N–30°S; 840 grid points) and the time period 1980–2006. Attribute diagrams (using relative observed frequency versus forecast probability) show the reliability of the forecasts, with perfect forecasts shown by a solid diagonal line and the distribution of forecasts among bins representing the resolution of the forecast system. Dots located in the shaded regions indicate positive forecast skill, and dots outside the dashed lines bordering the grey zones contribute to negative skill. We show attribute diagrams for the above-median forecasts and from the upper tercile.

Attribute diagrams for the above-median forecasts are shown in Fig. 7. Forecasts from DJF and MAM at LT=0 are slightly more reliable than forecasts from JJA and SON, with dots lying closer to the perfect reliability diagonal line. The forecasts in JJA and SON also show larger sized dots (higher proportion of forecasts in the middle region) indicating more climatological forecasts and less sharpness. All forecasts show a tendency to be overconfident, with lower forecast probabilities having a dry bias and higher forecast probabilities, a wet bias. With increasing LT, the four seasons have more forecasts near climatology (with larger dots between the forecast probabilities values of 0.4–0.6).

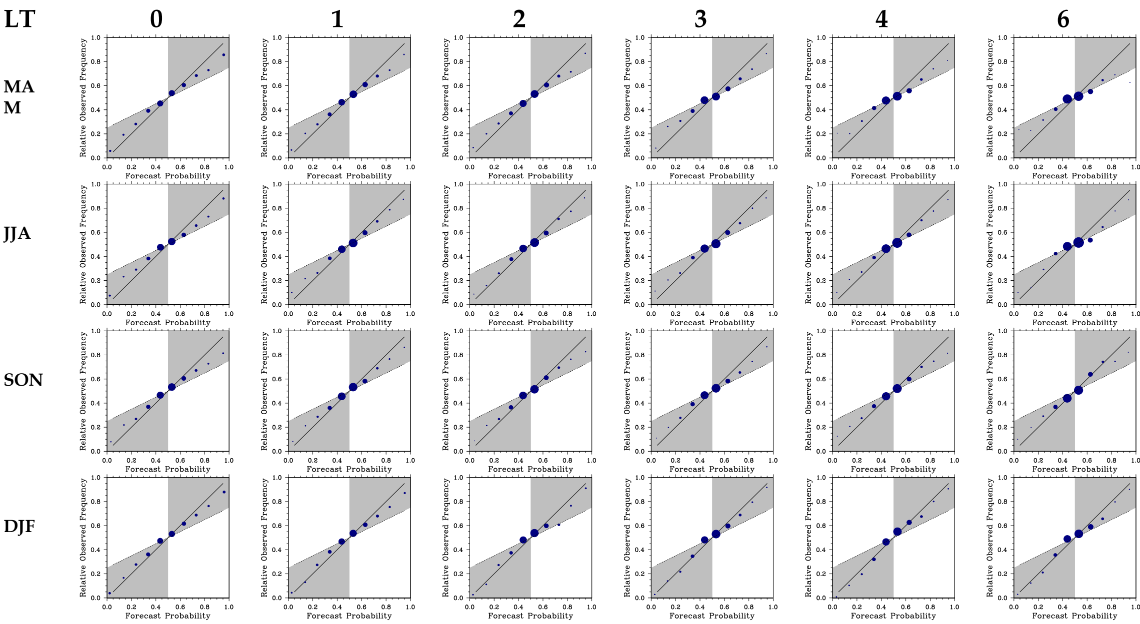

Fig. 7 Attributes diagrams for above-median forecasts from POAMA for the four austral seasons and six LTs for the Pacific region and the period 1980–2006. The grey region indicate forecasts with higher skill than a climatological forecast and the diagonal solid black line represents perfect reliability. The size of each dot is proportional to the total number of forecasts in each forecast probability bin (fixed width 0.1).

Attribute diagrams for the upper tercile forecasts are shown in Fig. 8. They show forecasts are overconfident and show a tendency to a climatology forecast with increasing LT (similar to the above-median forecasts). The most reliable forecasts with good resolution are from DJF at LT=0, followed by MAM. Attribute diagrams of the lower tercile forecasts (not shown) are very similar to those shown here for the upper terciles forecasts. However, the middle tercile forecasts are quite different and show forecasts which are less reliable than the lower or upper tercile forecasts. This has been described by other researchers including Van den Dool and Toth (1991).

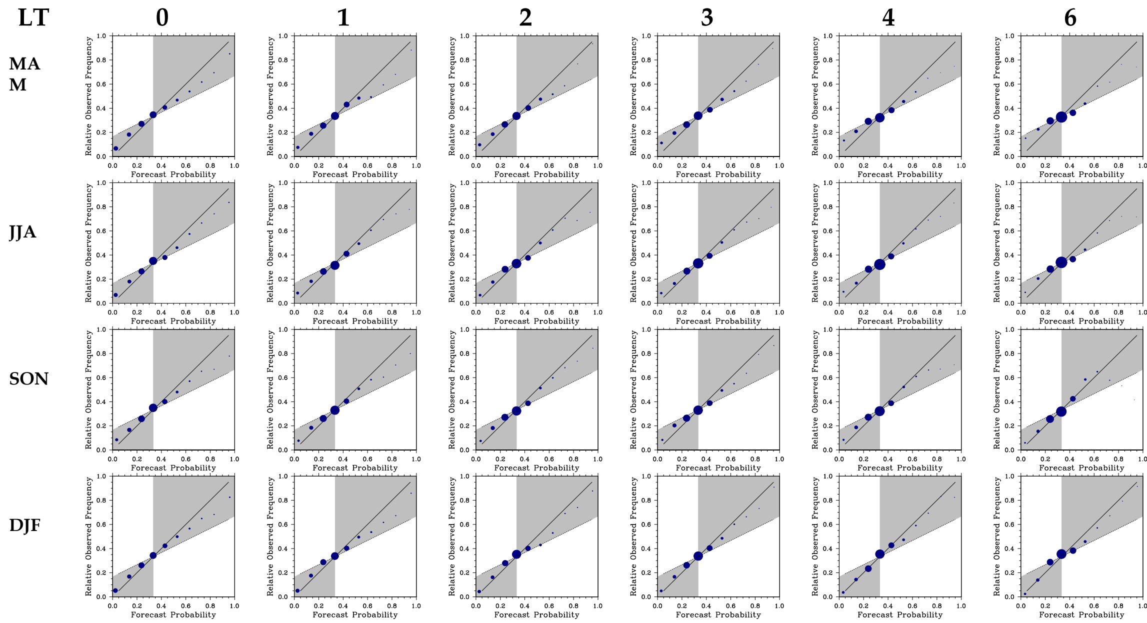

Fig. 8 Attributes diagrams for the upper tercile forecasts from POAMA for the four austral seasons and six LTs for the Pacific region and the period 1980–2006. The grey region indicate forecasts with higher skill than a climatological forecast and the diagonal solid black line represents perfect reliability. The size of each dot is proportional to the total number of forecasts in each forecast probability bin (fixed width 0.1).

5.6 Summary of the POAMA hindcast skill over the Pacific

An analysis of the highest tercile and above-median hit rates shows that they occur over the central tropical Pacific Ocean representing the ITCZ and the SPCZ. These hit rates are highest in DJF, when high to very high skill is attained over an elongated east-west region extending from Tarawa in Kiribati in the west to the Line Islands in the central Pacific, and north and south from the equator by about 7.5°. High skill also occurs over the Maritime continent and the Philippines region in most seasons. Although the skill slowly reduces with increasing LTs, it still remains moderately skilful to LT=6 months over much of the region for both the tercile and above-median hit rates. Typically the POAMA forecasts are overconfident and show a tendency towards climatology with increasing LTs.

6 STATION HINDCAST SKILL IN POAMA AND SCOPIC

In this section, we now compare the hindcast skill between POAMA and SCOPIC using tercile hit rates and ROC scores from the 14 Pacific stations.

6.1 Tercile hit rates

Hindcast forecasts from POAMA and SCOPIC for the 14 Pacific stations are used to calculate the tercile hit rates for the four austral seasons at a LT=1. For POAMA, the station value is the nearest grid point. Figure 9a shows the average tercile hit rates from POAMA (blue) and SCOPIC (green) for the period 1982–2006. This shows SCOPIC has slightly higher hit rates in DJF, MAM and SON with 45%, 37% and 46% respectively, compared to POAMA with 37%, 33% and 34%, but lower in JJA (35% versus 41%). Figure 9b shows the average tercile hit rates from SCOPIC for the two periods 1982–2006 (green) and 'All Years' (red). The tercile hit rates from 'All Years' are almost unchanged in DJF and JJA, but there is a small increase in skill in MAM (40%), and a small fall in SON (43%). In summary, the two periods used by SCOPIC from the 14 stations and four seasons have the same overall tercile hit rate of 41%. All average tercile hit rates from POAMA and SCOPIC for the two periods are at or above climatology (33.3%).

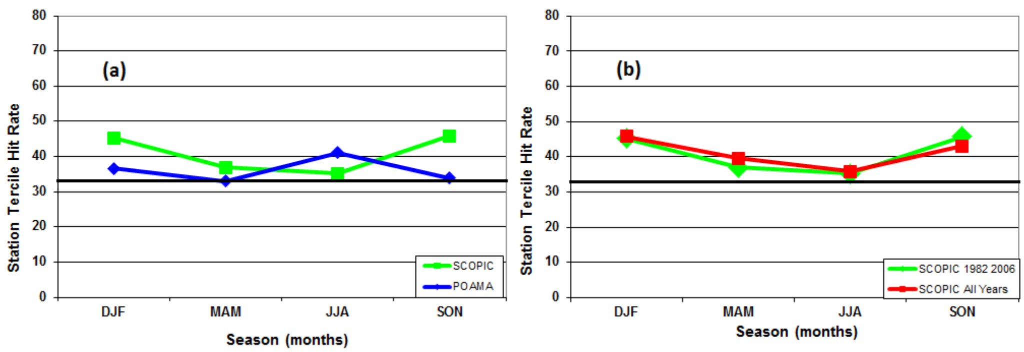

Fig. 9 Average tercile hit rates from (a) POAMA (blue) and SCOPIC (green) hindcast forecasts for 1982–2006 and (b) from SCOPIC for 1982–2006 (green) and 'All Years' (red) for the four austral seasons and a LT=1. The solid black horizontal line represents climatology (33.3%).

6.2 Tercile ROC scores

Hindcast forecasts from the 14 Pacific stations have been used to calculate the lower, middle and upper tercile ROC scores from POAMA and SCOPIC for the four austral seasons and the two periods 1982–2006 and 'All Years' (Fig. 10). ROC scores are shown in blue from POAMA and green/red from SCOPIC. A ROC score of 0.50 or above indicates positive skill and below 0.50, no skill.

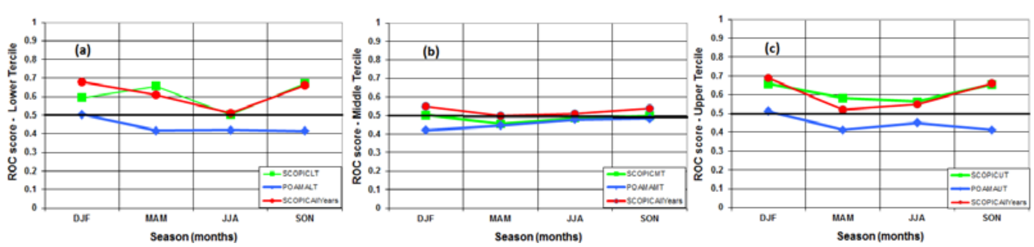

Fig. 10 Average tercile ROC scores from hindcast forecasts from POAMA (blue) and SCOPIC (green) for the period 1982–2006 and from SCOPIC for the period 'All Years' (red) for the four austral

seasons and LT=1 for (a) lower, (b) middle and (c) upper terciles. The solid black horizontal line represents climatology (0.50).

SCOPIC outperforms POAMA in both the lower and upper terciles, with all ROC scores higher than POAMA and above climatology. The highest ROC scores from SCOPIC are in SON from the lower tercile (LoT; 0.67) and in DJF from the upper tercile (UT; 0.66). The average difference of ROC scores between SCOPIC and POAMA for the LoT and UT is +0.17. However, the middle tercile (MT) ROC values are much closer in value between SCOPIC and POAMA, with an average difference of 0.03, and lie close to or just below climatology (0.50). POAMA achieves the highest ROC scores in DJF in the LoT and the UT, though these scores are only equivalent to the skill of a climatological forecast. The longer time series used by SCOPIC (red) increased the ROC scores marginally in DJF, with little change for other seasons and the MT.

6.3 Improving the hindcast skill in POAMA - nearest grid point versus interpolation

To assess whether the skill of POAMA could be improved at the station level, the calculation of rainfall from the forecast was modified from using the nearest grid point (NGP) to the method bilinear interpolation (BINT). BINT uses the values from the four nearest grid points and interpolation to determine the forecast at the station location. Average tercile ROC scores using forecasts from LT=1 from the 14 Pacific stations have been used to compare forecasts using the NGP and BINT. These are summarised in Fig. 11 (a-b).

Figure 11a shows the ROC scores have improved by 0.05–0.07 in each tercile when using BINT instead of the NGP, with the forecast skill now reaching ≥0.50, indicating positive skill. For individual stations, the lower tercile has the highest improvement in skill at Honiara (+0.01), Rotuma (+0.09) and Rarawai (+0.08). In the middle tercile, the highest improvement in skill is at Nuku'alofa (+0.11), Nabouwalu (+0.11), Alofi (+0.10) and Rotuma (0.09) and in the upper tercile from Port Moresby (+0.11), Honiara (+0.10) and Suva and Alofi with 0.07. In Fig. 11b, the ROC scores have improved by 0.05–0.08 across all seasons using BINT, with the highest improvement in JJA. The average ROC scores from DJF and JJA now have positive skill at 0.53 and with MAM and SON just below 0.50. The stations with the largest improvement in DJF are Funafuti and Honiara (+0.10) and Port Vila (+0.08). In MAM, the largest improvement in skill is at Rotuma (+0.13) and Alofi and Nabouwalu (+0.08); in JJA, Suva, Alofi and Port Moresby (+0.12), Honiara (+0.12) and Rotuma (+0.11) and in SON, Nuku'alofa (+0.13), Honiara (+0.09) and Rarawai and Apia (+0.08).

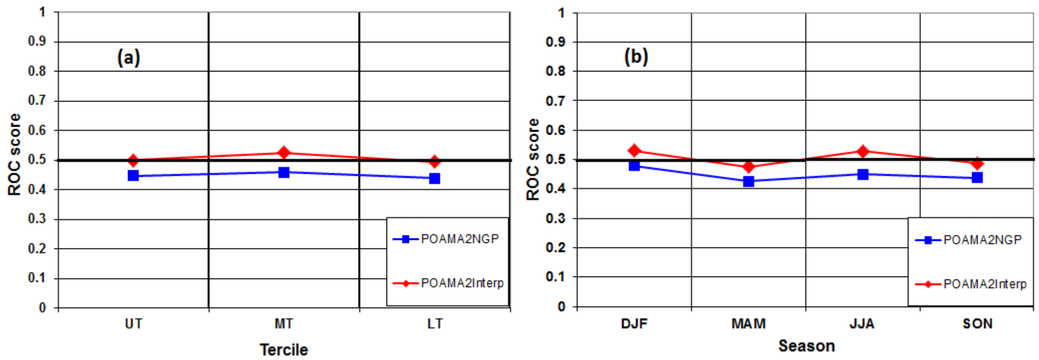

Fig. 11 Summary of the average tercile ROC scores from POAMA and LT=1 for the 14 Pacific stations using the nearest grid point (red) and bilinear interpolation (blue) for (a) for each tercile and (b) for the four austral seasons. The solid black line represents climatology (0.50).

In POAMA, the probabilistic tercile forecasts are calculated from the rainfall anomalies. The bilinear interpolation method BINT averages or 'smooths' out the probability values from grid points and reduces the spread or highest and most extreme values that can occur when only one grid point is used.

6.4 Improving the hindcast skill in SCOPIC - stratifying into ENSO years

As part of a study to investigate the skill from SCOPIC and LDA used to produce the seasonal forecasts, eight stations were selected from Kiribati (Tarawa), Samoa (Apia, Afiamalu and Faleolo) and Vanuatu (Port Vila, Anelgauhat, Pekoa and Sola) for a case study. The skill was then calculated after separating the training years in to three distinct sets representing El Niño, La Niña and neutral years. Using historical information from the SOI, Niňo3.4 and the 5VAR indices, the years were classified as El Niño, La Niña or neutral years for the time period 1950–2011. This provided 22 El Niño and 18 La Niña years, with the remaining 21 years neutral. Generally the minimum number of years needed to train the SCOPIC model using the LDA is 20–25 years (pers comm. David McClymont). Hit rates, ROC and LEPS percentage scores from SCOPIC were used to investigate the skill changes using these modified datasets.

An example of the skill scores using stratified data is shown in Table 3 from Tarawa (Kiribati). This shows that higher skill is obtained from SCOPIC when All Years are used to calculate the three different skill scores. The results using separate El Niño, La Niña and neutral years were not very encouraging, with generally lower skill occurring for all seasons. This typifies the results seen at the other stations, with a drop in skill for most lead times and seasons. Although this could be partly due to the shorter stratified time series, it seems more likely that using All Years provides positive benefits to the LDA, by increasing the range of rainfall outcomes across the full range of predictor values, as well as the various LTs.

Table 3 A comparison of the tercile hit rates, LEPS and ROCs scores from Tarawa (Kiribati) using SCOPIC and stratified data representing El Niño, La Niña and neutral years and All Years, using the predictor 5VAR from 1950–2011 for the four austral seasons and a LT=1. Bold values indicate positive skill.

Score Metric	Season	DJF	MAM	JJA	SON
Tercile Hit Rates	El Niño	28.6	19.0	**36.4**	9.1
	La Niña	29.4	23.5	**38.9**	**38.9**
	Neutral	**45.0**	**50.0**	**42.9**	**42.9**
LEPS	All Years	**70.5**	**54.1**	**34.4**	**62.9**
	El Niño	-5.6	-6.5	-3.2	-4.7
	La Niña	-6.8	-7.5	**15.9**	**10.5**
	Neutral	**8.0**	**28.0**	**5.4**	**15.1**
ROCS	All Years	**54.9**	**12.6**	**3.2**	**50.3**
Lower	El Niño	0.40	0.28	0.44	0.33
	La Niña	0.48	0.20	**0.56**	**0.62**
	Neutral	**0.69**	**0.85**	0.33	0.46
Middle	All Years	**0.93**	**0.76**	**0.55**	**0.91**
	El Niño	**0.57**	0.34	0.39	0.38
	La Niña	0.13	**0.55**	**0.52**	0.17
	Neutral	0.17	**0.63**	**0.59**	**0.62**
Upper	All Years	**0.69**	0.49	0.49	**0.64**
	El Niño	0.35	0.14	0.37	0.23
	La Niña	0.18	0.41	**0.79**	**0.71**
	Neutral	**0.68**	**0.73**	**0.73**	**0.79**
	All Years	**0.90**	**0.65**	**0.65**	**0.90**

An example of how the data stratification has reduced the forecast skill is shown in Fig. 12 for Tarawa (Kiribati) for 12 seasons and ten LTs. Figure 12a shows the tercile hit rates for All Years (1950–2011; 61 years) using the 5VAR index as the predictor. Good skill with longer LTs occurs at the start of the year, but this reduces to only two months by MJJ. The austral autumn is well known for its predictability barrier and is when the ENSO signal is least predictable (and when skill falls). The skill then improves progressively with each season up to DJF, at which time positive skill extends out to nine months. In Figures 12b and 12c, shows the stratified El Niño and La Niña years respectively, with the skill much lower than in Fig. 12a, with no systematic pattern across the different lead times and seasons. In Fig. 12d (showing neutral years), the skill is better than from El Niño or La Niña years (Fig. 12b and 12c), with more positive skill (blue), but not as high or in contiguous blocks as shown in Fig. 12a.

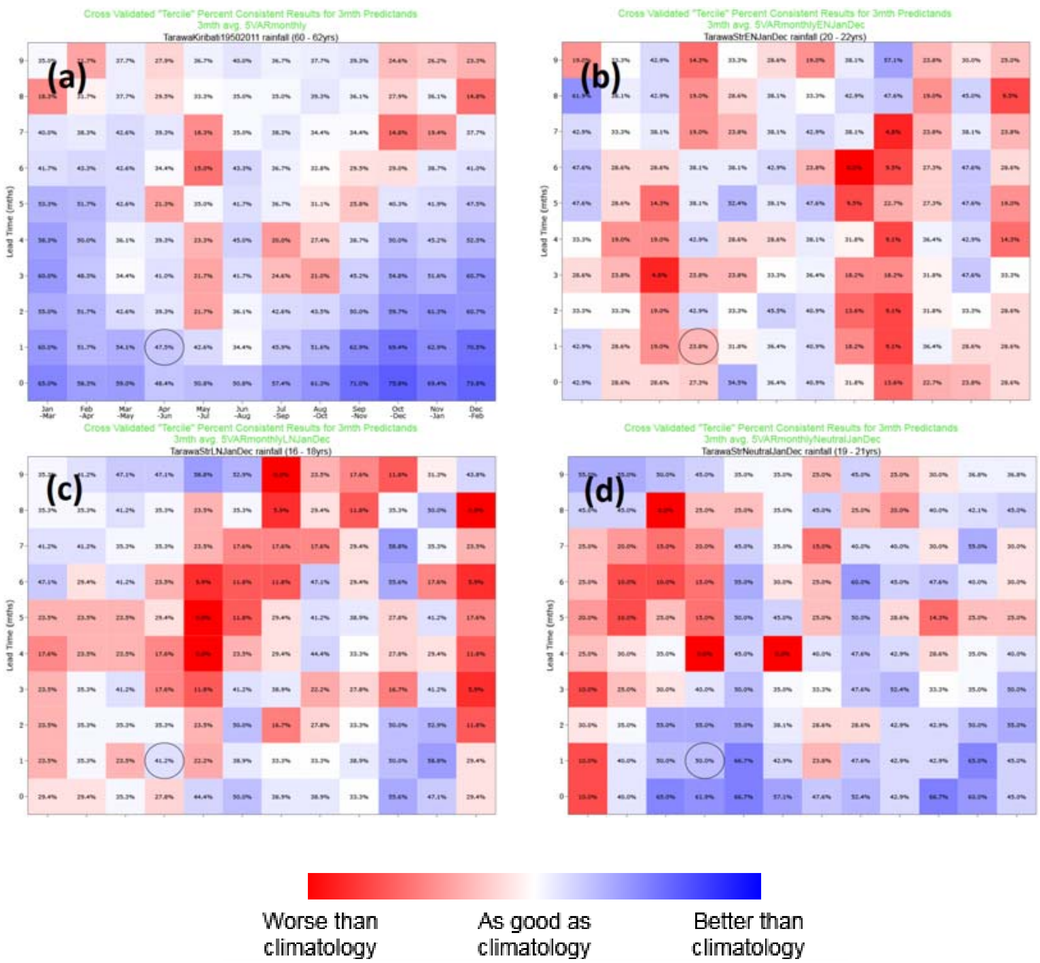

Fig. 12 Tercile hit rates from Tarawa (Kiribati) using the predictor 5VAR index for the 12 seasons and numerous LTs (zero to nine months) for (a) All Years (1950–2011); (b) 22 El Niño years; (c) 18 La Niña years and (d) 21 neutral years. Shades of blue represent positive skill and shades of red indicate negative or poor skill. Seasons start with JFM to DJF in Fig. 12a but MJJ to AMJ for Fig. 12 (b-d).

Across the other seven stations, the LEPS scores were the most strongly affected by the stratification into El Niño, La Niña or neutral years, with most seasons and LTs having lower or negative skill. Only Port Vila and Pokoa maintained several zones of positive LEPS skill and only in neutral years. ROC scores maintained some positive skill in neutral years in the lower and UT at Tarawa, Port Vila, Pekoa and Anelgauhat. Some skill also remained in the El Niño and La Niña years in the LoT at Faleolo, Apia and Afiamalu. Port Vila and Pekoa shows some skill in El Niño years and Sola and Pekoa in La Niña years in the MT. For the tercile hit rates, only Faleolo has some positive skill in La Niña years, and Port Vila and Pekoa, in the neutral years. In summary, it seems likely that neutral years probably retain some signals from a wider range in the 5VAR index and therefore shows positive skill in some seasons and lead times at some stations.

In summary, it is clear that in order to maximise the skill from SCOPIC at each station, the whole time series using rainfall and predictors is most appropriate, instead of stratifying the data into three distinct sets or groups based on ENSO. The stratifying of the data causes a major drop in skill for most seasons and LTs using tercile hit rates, LEPS percentage and ROC scores.

7 REAL-TIME STATION FORECASTS FROM POAMA AND SCOPIC

This section discusses the skill of seasonal forecasts from both POAMA and SCOPIC from 2012 and 2013.

7.1 Scored tercile forecasts

Scored values (%) from real-time seasonal forecasts (described in section 3.5) from POAMA and SCOPIC are shown in Fig. 13 for 2012 and 2013 for the 20 seasons and 13 stations using a LT=1. There are 221 forecasts from the 20 seasons (an average of 11 forecasts per season), with some countries not always reporting the verification of forecasts. Figure 13 shows that POAMA has slightly higher skill in the scored forecasts during 2012, compared to SCOPIC, with more varied skill scores from POAMA and SCOPIC during 2013. Forecasts from POAMA have the highest skill in JAS (74%) in 2012 and JJA (80%) in 2013, with high skill (≥60%) also in FMA, ASO and SON in 2012, and JAS and ASO in 2013. SCOPIC has the highest skill in ASO (67%) in 2012 and JJA (70%) in 2013, with high skill in JAS and OND in 2012, and FMA for both years. The lowest skill in the POAMA forecasts occurred in MAM and MJJ (30%) in 2013 and from SCOPIC in JFM (22%) in 2012 and ASO (31%) in 2013. Both forecast systems show similar increases and decreases in skill from one season to another. Both systems have slightly higher skill in the austral winter and spring and lower skill in austral summer and autumn. Overall, POAMA achieved an average score for the 20 seasons and 221 forecasts of 57%, compared to SCOPIC with 50%. Hence, both forecast systems provide positive skill above climatology (44.4%).

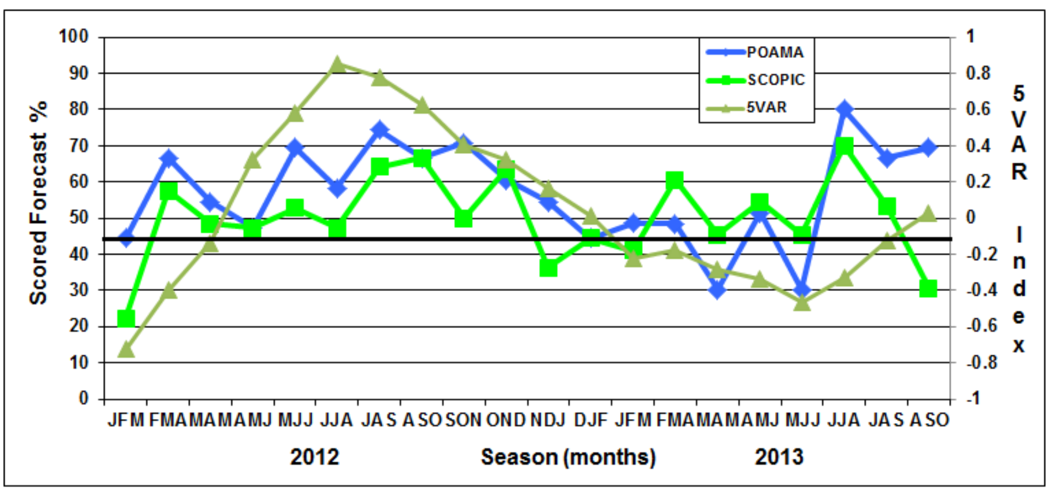

Fig. 13 Scored tercile forecasts from POAMA (blue), SCOPIC (green) and the 5VAR index (olive) from 13 Pacific stations and 20 seasons (221 forecasts) and a LT=1 from JFM 2012 to ASO 2013. The solid black line represents climatology (44.4%) and forecasts above this line have positive skill.

During the first few months of 2012, tropical Pacific climate was dominated by La Niña conditions (with negative 5VAR values), followed by a change to borderline El Niño conditions by mid-year, with positive 5VAR values (Fig. 13). By the end of the 2012, conditions in the tropics were more neutral with near-zero 5VAR values, which became weakly negative during 2013. This suggests the real-time forecasts have positive skill in both La Niña and El Niño 'like' conditions, as well as during neutral periods.

7.2 Tercile Hit Rates

Tercile hit rates from POAMA and SCOPIC are shown in Fig. 14 for 2012 and 2013 for the 20 seasons and 13 stations using a LT=1. Tercile hit rates from POAMA are higher for most seasons than from SCOPIC in 2012, but lower from FMA to AMJ in 2013. The highest tercile hit rates from POAMA are from JFM (67%) in 2012 and JJA (70%) in 2013, with high skill (>60%) in JAS and SON. The highest tercile hit rates from SCOPIC are in ASO (54%) in 2012 and JJA (60%) in 2013, with moderate skill (40–60%) in JAS and OND in 2012 and FMA in 2013. Similar to the scored forecasts, the skill is higher at the start of 2012 and in the austral winter and spring and lower in the austral autumn. Overall, POAMA has the highest average tercile hit rate for 20 seasons and 221 forecasts, with 44%, compared to SCOPIC with 33%, which are both above climatology.

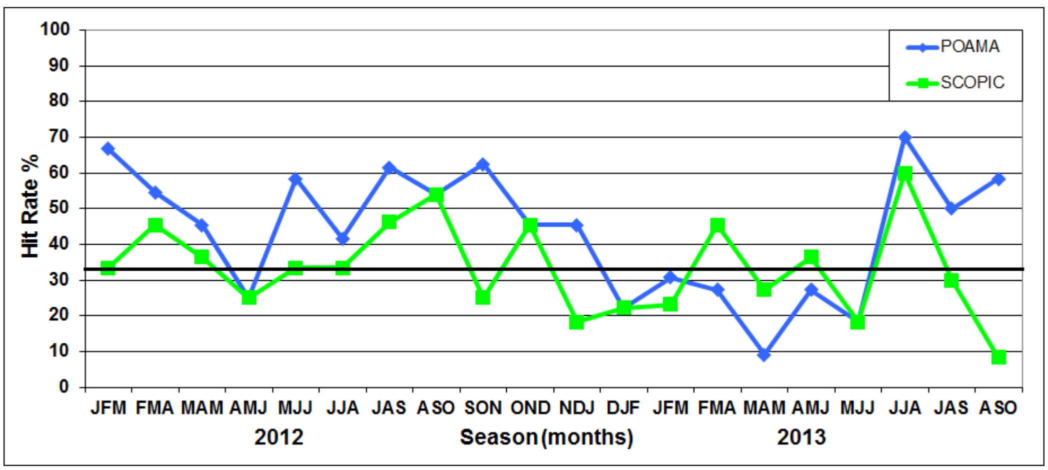

Fig. 14 Tercile hit rates from POAMA (blue) and SCOPIC (green) for 13 Pacific stations and 20 seasons (221 forecasts) and a LT=1 from JFM 2012 to ASO 2013. The solid black line represents climatology (33.3%), with forecasts above this line having positive skill.

7.3 LEPS scores

The LEPS scores from POAMA and SCOPIC are shown in Fig. 15 for 2012 and 2013 for 20 seasons and 13 stations using a LT=1. LEPS scores show the accuracy of tercile seasonal forecasts compared to a climatological forecast. Forecasts with positive LEPS scores indicate good skill, whereas negative LEPS scores indicate no skill. LEPS score range from -1 to 1 (perfect forecasts; Jolliffe and Stephenson (2012)). LEPS scores from POAMA are more variable than from SCOPIC, with the highest skill in JFM, FMA, JJA and JAS in 2012 and JJA in 2013. POAMA forecasts with poor skill (below zero) occur in MAM, AMJ from both 2012 and 2013 and in DJF. SCOPIC has the highest LEPS scores in FMA in 2012 and negative LEPS scores in MAM, NDJ and DJF in 2012 and ASO in 2013. Interestingly, the LEPS scores with the lowest skill from POAMA and SCOPIC occur during the same seasons (MAM and DJF) and also with the highest skill in FMA of 2012. Again, similar to the scored forecasts and tercile hit rates, LEPS scores are higher in the austral summer and winter from both POAMA and SCOPIC, and lower in the austral autumn and spring. Overall, the forecasts from POAMA have slightly higher LEPS scores than SCOPIC, with +0.013 compared to +0.003 respectively indicating positive skill from both forecast systems. The larger range in the LEPS scores shown from POAMA indicates the more emphatic forecasts, (i.e. the probabilities are higher in the correct tercile). In contrast, SCOPIC has more forecasts closer to climatology and hence the resultant LEPS scores are closer to zero.

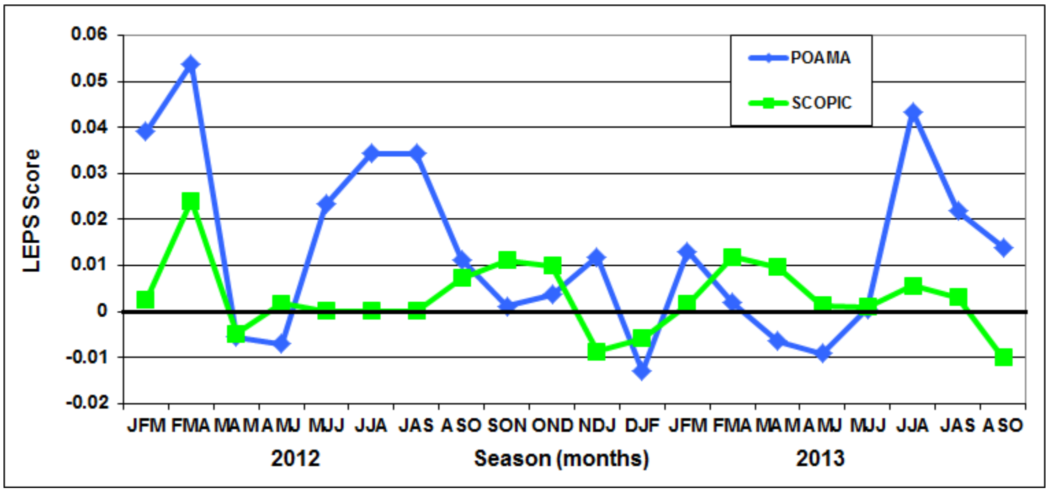

Fig. 15 LEPS scores from POAMA (blue) and SCOPIC (green) for the 13 Pacific stations and 20 seasons (221 forecasts) and a LT=1 from JFM 2012 to ASO 2013. A LEPS scores above zero (black line) indicates positive skill and below zero, no skill.

7.4 Regional variations of skill in the Pacific from POAMA and SCOPIC

Although we have used three skill scores (scored forecasts, tercile hit rates and LEPS scores) to describe the skill of POAMA and SCOPIC from real-time forecasts, it is also useful to describe the regional variations to highlight high or low skill from different seasons and the 13 stations. Regional variations in skill in POAMA were described by Cottrill et al. (2013), by comparing the predicted ensemble rainfall with satellite observations (CMAP) and also in section 5.1.

The Pacific island stations with the highest number of correct tercile forecasts (>50%) from POAMA are from Tarawa (Kiribati), Nadi Airport (Fiji), Apia and Faleolo (Samoa) and (Wewak) Papua New Guinea. Other stations with moderate skill (40–50%) are Funafuti (Tuvalu), the Honiara (Solomon Islands) and Port Moresby (Papua New Guinea). The lowest skill (≤25%) from POAMA is at Port Vila (Vanuatu) and Rotuma (Fiji) with the lowest number of correct forecasts. For 2012 and 2013, no stations from SCOPIC had high skill averaging 50% or higher. However, moderate skill (40–50%) occurred at the Rarotonga (Cook Islands), Alofi

(Niue), Tarawa (Kiribati), Port Vila (Vanuatu) and Honiara (Solomon Islands). Low skill (≤25%) occurs at Nuku'alofa (Tonga), Port Moresby (Papua New Guinea) and Faleolo (Samoa). Some stations have observations missing during the period from 2012–2013, and this may affect the verification results at these stations. This highlights the importance of maintaining basic daily and monthly observations of rainfall for forecast verification in the Pacific Islands and can also help to identify regions where the climate is not well simulated in dynamical models like POAMA.

7.5 Summary of Real-time forecasts

Real-time verification results indicate that scored forecasts and tercile hit rates are highest in the austral winter and early spring and lowest skill in late austral summer or autumn. The LEPS scores vary much more between POAMA and SCOPIC, but show that the lowest values generally occur in the early austral summer and autumn. Although we have examined only a short period using real-time forecasts, these do provide a useful insight to the overall performance of the two forecast systems in the Pacific region.

These results are generally consistent with results from Cottrill et al. (2013), with higher skill occurring along the equatorial region (such as at Kiribati) and other parts of the southwest Pacific associated with the SPCZ (Fiji, Samoa and the Solomon Islands). Overall, POAMA seems to outperform SCOPIC using these 13 stations over the relatively short period of real-time forecasts. However, 2012–2013 showed considerable climate variability in the state of the ocean and atmosphere, which had important implications for the skill of the seasonal forecasts. La Niña conditions prevailed early in 2012 (Martin 2013), followed by warming conditions in the tropical Pacific, with SSTs reaching a peak in August, indicating marginal El Niño conditions. From October 2012 until ASO in 2013, near neutral conditions prevailed in the tropical Pacific and both POAMA and SCOPIC generally maintained skilful forecasts during this time.

8 DISCUSSION AND CONCLUSIONS

We have examined the skill from two different seasonal forecast systems used at the BoM, the dynamical model POAMA and the statistical model SCOPIC. Both are being used in the Pacific region to increase the capacity of NMS to provide seasonal forecasts, not only for assisting with advanced warnings of climate extremes, such as floods and droughts associated with El Niño and La Niña events, but to provide better predictions of rainfall and other climate elements in neutral years to increase the resilience of Pacific nations to climate extremes. The range of stakeholders using seasonal forecasts is not limited just to local NMS from the Pacific, but a whole range of resource managers who require information for better decision making (Hartmann et al. 2002; Potgieter et al. 2003; Kuleshov et al. 2012), such as the multi-million dollar skipjack tuna fishery, which is sensitive to ENSO variations (Lehodey et al. 2006).

We showed the correlation between station rainfall from the Pacific Islands and the 5VAR index is strongly positive in the equatorial region (Kiribati) and moderate or strongly negative in the SPCZ (Fiji, Tonga, Samoa and) and the southwest Pacific (Vanuatu) regions. This reflects the distinct rainfall changes across tropical Pacific which occur during El Niño and La Niña events, similar to results using the Niňo3.4 index (Cottrill et al. 2012). This indicates that both the 5VAR and Niňo3.4 indices would be useful as predictors in SCOPIC for seasonal forecasts in the Pacific region (Cottrill and Kuleshov 2014).

In this report, we analysed the hindcast forecasts over the western and tropical Pacific region using LTs from zero to six months and all 12 seasons for the period 1980–2006. Cottrill et al. (2013) showed the correlation of predicted mean ensemble rainfall from POAMA and CMAP using a LT=0, with high skill over the central equatorial Pacific for the four austral seasons. Our results using a LT=1 show that the high skill continues into the second month of the forecast in much of the central tropical Pacific, as well as the Maritime continent, the Philippines region and parts of the southwest Pacific. Further, tercile and above-median hit rates show good skill in these regions for LTs up to six months and most seasons. This suggests the extension of seasonal forecasts into the Indonesian and Philippines region using POAMA and other dynamical models is a viable proposition, with potentially large benefits for the two highly populated countries.

In the Australian region, Lim et al. (2010a) showed that the highest skill (using proportion correct) from POAMA was in ASO and SON, with good skill also in JFM, MAM, and MJJ and the lowest skill in OND, NDJ and DJF. Our results are similar (north of 30°S), with the highest skill occurring in JFM and MJJ and the lowest skill in AMJ and OND. However, DJF is opposite, with higher skill shown by this study. At longer LTs, the highest skill is in JFM and FMA, compared to MAM, ASO, SON and OND by Lim et al. (2010a), with both studies showing the lowest skill in the austral winter (MJJ, JJA and JAS). Langford and Hendon (2011) showed SON has the highest skill at longer LTs using the four austral seasons and three international GCMs and POAMA. However, they did not discuss how the other eight seasons may have performed. The reliability of the seasonal forecasts over the Pacific region is quite similar to that shown over Australia (Lim et al. 2010a; Langford and Hendon 2011), with forecasts tending towards climatology and less sharpness at longer LTs.

The forecast skill in dynamical models using short LTs is expected to be fairly continuous between seasons, with only small changes, since two months of the new forecast overlaps the previous forecast. However, Lim et al. (2010a) showed prominent see-saw patterns in the proportion correct values from DJF to JAS (seven seasons) over Australia, suggesting that model errors may be a cause, indicating the potential forecast skill in this period has yet to be realised by POAMA. The lower skill in the austral late spring and summer (OND, NDJ and DJF) and the smaller changes in the skill between the seasons (Lim et al. 2010a) seems more realistic and may represent real climatological changes associated with the higher rainfall variability over Australia during the Australian monsoon (Wang et al. 2008a). Overall, the skill scores obtained over Australia in this study using hit rates are slightly higher than those achieved by using the proportion correct method used by Lim et al. (2010a).

The forecast skill using hindcast forecasts at the station level was examined for two periods from SCOPIC and one period from POAMA. Clearly the hindcast period is important for determining the skill of the forecasts (Barnston et al. 2012). We showed that using a longer hindcast period in SCOPIC did not improve the overall skill, but note that inherent decadal ENSO variability (Power et al. 2006) can be important. Overall, SCOPIC has slightly higher skill than POAMA using tercile hit rates except in JJA, where POAMA is higher, with most stations at or above climatology. ROC scores are higher in SCOPIC in the lower and upper tercile than POAMA, but are more similar in the middle tercile, with most ROC scores from SCOPIC above climatology but slightly below in POAMA. To improve the skill scores from POAMA, BINT was shown to improve rainfall skill at the station level, with an improvement of 5–7% across all seasons and terciles. However, stratifying the data in SCOPIC based on ENSO reduced the skill of most forecasts.

Real-time forecasts from 2012–2013 (assessed using scores, tercile hit rates and LEPS scores) showed that POAMA has slightly higher skill than SCOPIC, although most forecasts were generally above climatology for 2012 and near climatology for 2013. LEPS scores are more highly variable from POAMA than from SCOPIC, with both forecast systems generally showing positive skill for most seasons. This indicates that the more emphatic forecasts from POAMA are providing improved skill compared to SCOPIC, which has more forecasts near climatology and lower LEPS scores. Barnston et al. (2012) also showed dynamical models have improved skill over their statistical counterparts when predicting ENSO, even when short periods of real-time forecasts were utilised.

Although the climate variability in the tropical Pacific region is dominated by ENSO and El Niño and La Niña events, POAMA is able to simulate the location and intensity of the SPCZ and the ITCZ fairly well in all years, not just the major excursions during these events (Charles et al. 2013a). The skill of real-time forecasts shown by POAMA and SCOPIC during the predominantly neutral years 2012 and 2013 supports this conclusion. For any statistical or dynamical forecast system to be a useful tool, it must be able to predict not just the major rainfall changes between El Niño and La Niña events but also during neutral years and we have shown that both POAMA and SCOPIC can achieve this.

The continued use and development of the SCOPIC model seems assured for a number of years under the COSPPac project, which has recently been extended to June 2016 (COSPPac 2012). The dynamical model POAMA, which is used extensively in Australia for seasonal climate research and applications, is being continuously improved and will be eventually replaced by the Australian Community Climate and Earth-System Simulator or ACCESS, which will provide seamless forecasts across a range of time spans from days to many months in the near future (BoM 2012; Zhao et al. 2013).

ACKNOWLEDGMENTS

The research in this paper was conducted through the PASAP and ongoing support from PACCSAP, supported by the AusAID and the Department of Climate Change and Energy Efficiency and delivered by the Bureau of Meteorology and CSIRO. We also acknowledge the COSPPac group for providing the seasonal forecasts from SCOPIC and continued support in the monthly OCOFs. We also acknowledge the Pacific Island countries for rainfall data and the seasonal forecasts available through the PASAP web portal.

REFERENCES

Abawi, G.Y., Dutta, S., Zhang, X. and McClymont, D. Eds. (2005a). ENSO based streamflow forecasting and its application to water allocation and cropping decisions-An Australian experience. Regional Hydrological Impacts of Climatic Change-Impact Assessments and Decision Making. Wallingford, IAHS Publication.

Abawi, Y., Lianso, P., Harrison, M. and Mason, S.J. (2005b). Water, Health and Early Warnings. Seasonal Climate: Forecasting and Managing Risk. A. Troccoli, M. Harrison, D. L. T. Anderson and S. J. Mason, Springer: 351-395.

Barnston, A.G. and Ropelewski C.F. (1992). "Prediction of ENSO episodes using canonical correlation analysis." *J. Climate* 5: 1316-1345.

Barnston, A.G., Tippett, M.K., L'Heureux, M.L., Li, S. and DeWitt, D.G. (2012). "Skill of Real-time Seasonal ENSO Model Predictions during 2002-2011 - Is Our Capability Increasing? ." *Bull. Am. Meteror Soc* 93: 631-651.

BoM. (2012). NMOC Operations Bulletin Number 93 - APS1 upgrade of the ACCESS-G Numerical Weather Prediction system. Bureau of Meteorology: 30 pp.

Brown, J.R., Power, S., Delage, F., Colman, R., Moise, A. and Murphy, B. (2011). "Evaluation of the South Pacific Convergence Zone in IPCC AR4 Climate Model Simulations of the Twentieth Century." *J. Climate* 24: 1565-1582.

Charles, A.N., Brown, J., Cottrill, A., Shelton, K.L., Nakaegawa, T. and Kuleshov, Y. (2013a). "The seasonal prediction of the South Pacific Convergence Zone in the Austral wet season." J. Geophys. Res. (In Prep.).

Charles, A.N., Cottrill, A., Jones, D., Hendon, H., Kuleshov, Y., Langford, S., Lim, E.-P., Shelton, K.L. and De Wit, R. (2013b). "Climate Prediction Capacities Strengthened in the National Meteorological Services: Pacific Adaptation Strategy Assistance Program Output 6 (PASAP-6)." Final Summary Project Report for the Department of Climate Change and Energy Efficiency and International Climate Change Adaptation Initiative: 22pp.

Charles, A.N., McClymont, D., d. Wit, R. and Jones, D. (2011). A software architecture for seasonal climate forecasts in the tropical Pacific. MODSIM11 International Congress on Modelling and Simulation Perth, Western Australia, December 2011, Modelling and Simulation Society of Australia and New Zealand.

Colman, R., Deschamps, L., Naughton, M., Rikus, L., Sulaiman, A., Puri, K., Roff, G., Sun, Z. and Embury, G. (2005). "BMRC Atmospheric model (BAM) version 3.0: comparison with mean climatology." *BMRC Research Report* No. 108: 1-23.

COSPPac. (2012). Climate and Oceans Support Program in the Pacific. Program Design Document, Bureau of Meteorology: 105 pp.

Cottrill, A., Hendon, H.H., Lim, E.-P., Langford, S., Kuleshov, Y., Charles, A. and Jones, D. (2012). "Seasonal Climate Prediction in the Pacific using the POAMA coupled model forecast system." *CAWCR Technical Report No. 048*: 1-22.

Cottrill, A., Hendon, H.H., Lim, E.-P., Langford, S., Shelton, K., Charles, A., McClymont, D., Jones, D. and Kuleshov, Y. (2013). "Seasonal Forecasting in the Pacific using the coupled model POAMA-2." *Wea. Forecasting* 28: 668-680.

Cottrill, A. and Kuleshov, Y. (2014). "Seasonal forecast skill from SCOPIC using different predictors." *Aust. Meteor.Ocean. J*. Submitted.

Drosdowsky, W. and Chambers, L.E. (2001). "Near-Global Sea Surface Temperature Anomalies as Predictors of Australian Seasonal Rainfall." *J. Climate* 14 (7): 1677.

Hartmann, H.C., Pagano, T.C., Sorooshian, S. and Bales, R. (2002). "Confidence Builders Evaluating Seasonal Climate Forecasts from User Perspectives." *Bull. Am. Meteror. Soc*. 83: 683-698.

Hudson, D., Alves, O., Hendon, H.H. and Marshall, A.G. (2011). "Bridging the gap between weather and seasonal forecasting: intraseasonal forecasting for Australia." *Quart. J. Roy. Meteor. Soc.* 137: 673-689.

Hudson, D., Marshall, A.G., Yin, Y., Alves, O. and Hendon, H.H. (2013). "Improving intraseasonal prediction with a new ensemble generation strategy." *Mon. Wea. Rev*. (doi.org/10.1175/MWR-D-13-00059.1).

Johnson, C. and Bowler, N. (2009). "On the Reliability and Calibration of Ensemble Forecasts." *Mon. Wea. Rev*. 137: 1717-1720.

Jolliffe, I.T. and Stephenson, D.B. Eds. (2003). *Forecast Verification*: A Practitioner's Guide in Atmospheric Sciences, John Wiley & Sons Ltd.

Jolliffe, I.T. and Stephenson, D.B. Eds. (2012). *Forecast Verification*: A Practitioner's Guide in Atmospheric Science, Wiley-Blackwell.

Kuleshov, Y., et al. (2012). "Pacific Adaptation Strategy Assistance Program: Strengthening the capacity for seasonal prediction services in Pacific countries." *Bull. Aust. Met.Ocean. Soc*. 25 (1): 7-12.

Kuleshov, Y., Qi, L., Fawcett, R. and Jones, D. (2008). "On tropical cyclone activity in the Southern Hemisphere: Trends and the ENSO connection." *Geophys. Res. Lett*. 35: L14S08, doi:10.1029/2007GL032983.

Langford, S. and Hendon, H.H. (2011). "Assessment of international seasonal rainfall forecasts for Australia and the benefit of multi-model ensembles for improving reliability." *CAWCR Technical Report No. 39*: 1-32.

Langford, S. and Hendon, H.H. (2013). "Improving Reliability of Coupled Model Forecasts of Australian Seasonal Rainfall." *Mon. Wea. Rev.* 141: 728-741.

Lee, T. and McPhaden, M.J. (2010). "Increasing intensity of El Niňo in the central-equatorial Pacific." *Geophys. Res. Lett.* 37 (L14603): doi:10.1029/2010GL044007.

Lehodey, P., et al. (2006). "Climate Variability, Fish, and Fisheries." *J. Climate* 19: 5009-5030.

Lim, E.-P., Hendon, H.H., Alves, O., Yin, Y., Wang, G., Hudson, D., Zhao, M. and Shi, L. (2010a). "Dynamical seasonal prediction of tropical Indo-Pacific SST and Australian rainfall with improved ocean initial conditions." *CAWCR Technical Report No. 032*: 1-26.

Lim, E., Hendon, H.H., Anderson, D.L.T., Charles, A. and Alves, O. (2010b). "Dynamical, statistical-dynamical and multi-model ensemble forecasts of Australian spring season rainfall." *Mon. Wea. Rev*. 139: 958-975.

Martin, L. (2013). "Seasonal climate summary southern hemisphere (autumn 2012): The transition from La Niña to neutral." *Aust. Meteor.Ocean. J.* 61 (1): 249-259.

Mendelssohn, R., Bograd, S.J., Schwing, F.B. and Palacios, D.M. (2005). "Teaching old indices new tricks: A state-space analysis of El Niňo related climate indices." *Geophys. Res. Lett*. 32 (L07709): doi:10.1029/2005GL022350.

Potgieter, A.B., Everingham, Y.L. and Hammer, G.L. (2003). "On measuring quality of a probabilistic commodity forecasts for a system that incorporates seasonal climate forecasts." *Int. J. Climatol*. 23: 1195-1210.

Potts, J.M., Folland, C.K., Jolliffe, I.T. and Sexton, D. (1996). "Revised "LEPS" Scores for Assessing Climate Model Simulations and Long-Range Forecasts." *J. Climate* 9 (1): 34-53.

Power, S., Haylock, M., Colman, R. and Wang, X. (2006). "The Predictability of Interdecadal Changes in ENSO Activity and ENSO Teleconnections." *J. Climate* 19 (19): 4755-4771.

Ramesh, N. and Murtugudde, R. (2013). "All flavours of El Niňo have similar early subsurface origins." *Nature Climate Change* 3 (doi:10.1038/nclimate1600): 42-46.

Schiller, A., Godfrey, J., McIntosh, P., Meyers, G., Smith, N., Alves, O., Wang, O. and Fiedler, R. (2002). "A new version of the Australian community ocean model for seasonal climate prediction." CSIRO Marine Research Report No.240: 82 pp.

Schroeder, T.A., Chowdhury, M.R., Lander, M.A., Guard, C.C., Felkley, C. and Gifford, D. (2012). "The Role of the Pacific ENSO Applications Climate Center in Reducing Vulnerability to Climate Hazards." *Bull. Am. Meteror Soc*: 1003-1015.

Sooraj, K.P., Annamalai, H., Kumar, A. and Wang, H. (2012). "A Comprehensive Assessment of CFS Seasonal Forecasts over the Tropics." *Wea. Forecasting* 27 (1): 3-27.

Van den Dool, H.M. and Toth, Z. (1991). "Why do Forecasts for "near normal" often fail?" *Wea. Forecasting* 6: 76-85.

Vincent, E.M., Lengaigne, M., Menkes, C.E., Jourdain, N., Marchesiello, P. and Madec, G. (2011). "Interannual variability of the South Pacific Convergence Zone and implications for tropical cyclone genesis." *Climate Dyn*. 36: doi:10.1007/s00382-00009-00716-00383.

Wang, B., Lee, J.Y., Kang, I.S., Shukla, J., Kug, J.S., Kumar, A., Schemm, J., Luo, J.J., Yamagata, T. and Park, C.K. (2008a). "How accurately do coupled climate models predict the leading modes of Asian-Australian monsoon interannual variability?" *Climate Dyn*. 30: 605-619.

Wang, G., Alves, O., Hudson, D., Hendon, H.H., Liu, G. and Tseitkin, F. (2008b). "SST skill assessment from the new POAMA-1.5 system." Bureau of Meteorology Research Letters 8: 2-6.

Wang, W., Chen, M. and Kumar, A. (2010). "An assessment of the CFS Real-Time Seasonal Forecasts." *Wea. Forecasting* 25: 950-969.

Wilks, D.S. (2006). *Statistical Methods in the Atmospheric Sciences*, Elsevier.

Xie, P. and Arkin, P.A. (1997). "Global Precipitation: A 17 -Year Monthly Analysis Based on Gauge Observations, Satellite Estimates, and Numerical Model Outputs." *Bull. Amer. Meteor. Soc.* 78 (11): 2539-2558.

Yin, Y., Alves, O. and Oke, P.R. (2011). "An Ensemble Ocean Data Assimilation System for Seasonal Prediction." *Mon. Wea. Rev.* 139: 786-808.

Zhang, C., Dong, M., Gualdi, S., Hendon, H.H., Maloney, E.D., Marshall, A., Sperber, K.R. and Wang, W. (2006). "Simulations of the Madden-Julian oscillation in four pairs of coupled and uncoupled models." *Climate Dyn*. 27: 573-592.

Zhao, M., Roff, G., Hendon, H.H., Okely, P., Zhou, X., Marshall, A.G., Liu, G., Tseitkin, F. and Alves, O. (2013). "Improving Multiweek Rainfall Forecasts: Experiments with the ACCESS climate models." *CAWCR Technical Report No. 064*: 1-44.

APPENDIX A

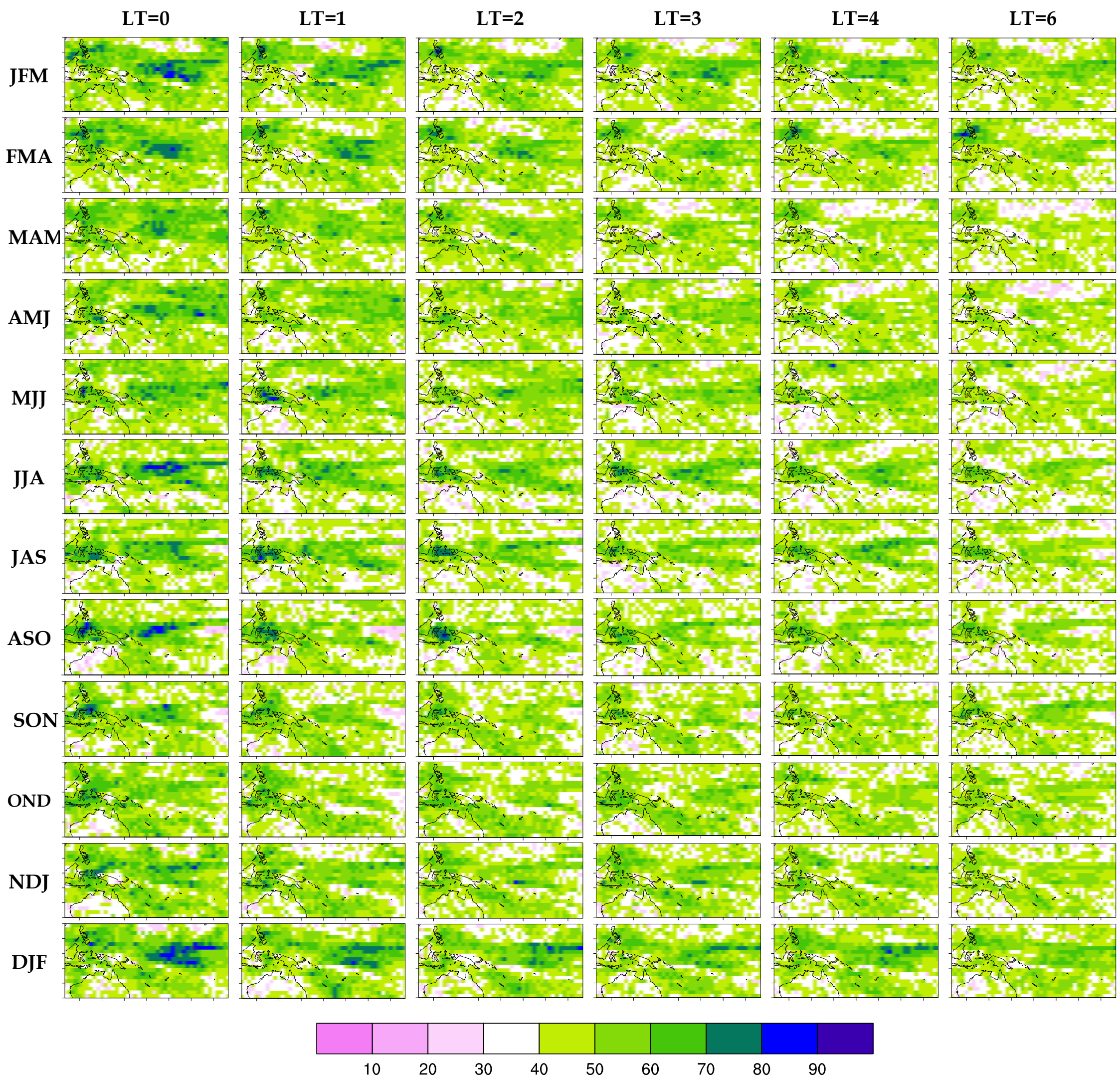

Fig. 16 Tercile Hit Rates of Rainfall from POAMA2 (P24)

APPENDIX B

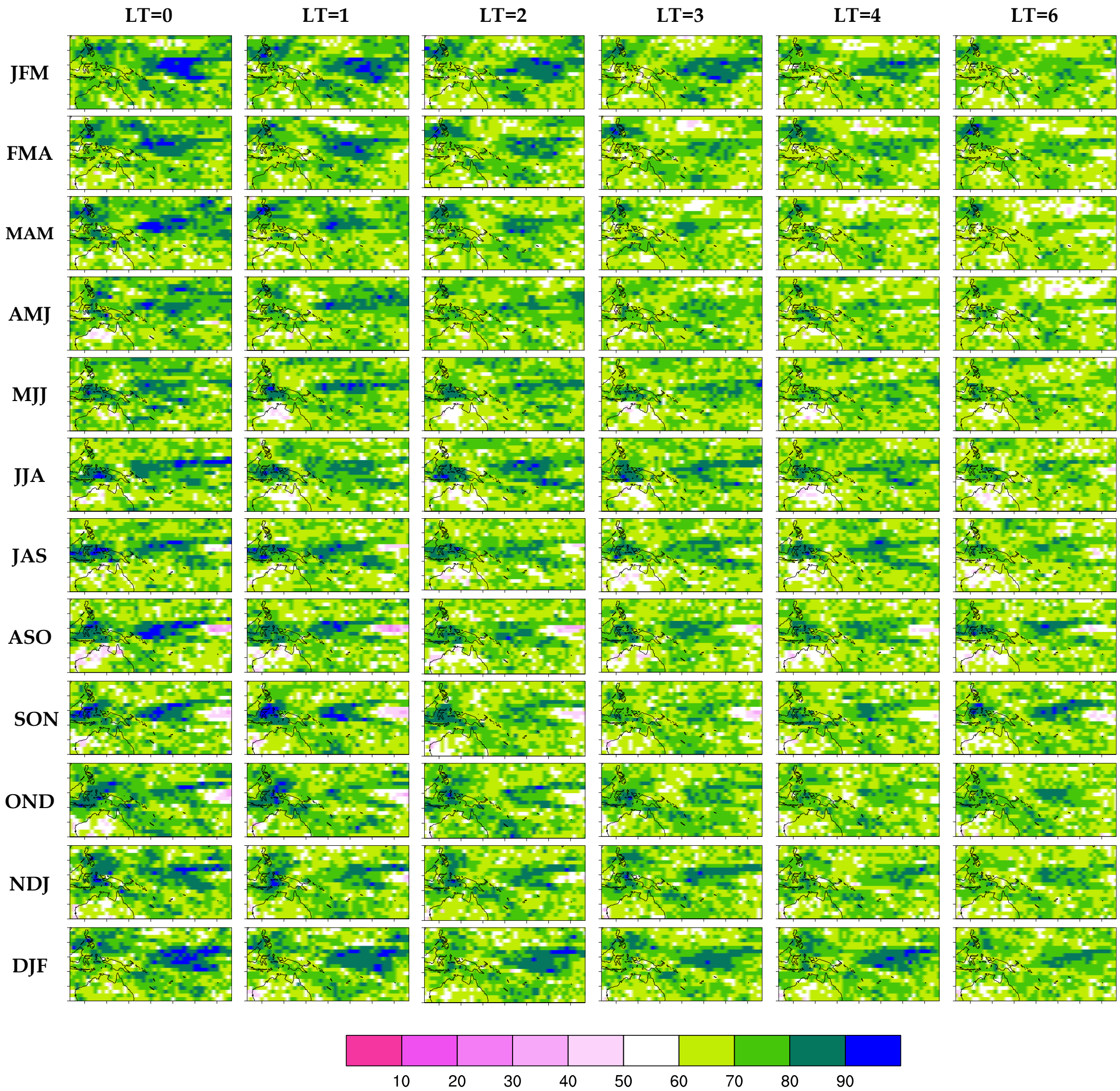

Fig. 17 Above-Median Hit Rates of Rainfall from POAMA2 (P24)

The Centre for Australian Weather and Climate Research is a partnership between CSIRO and the Bureau of Meteorology.