Dynamical Forecast of Inter–El Niño Variations of Tropical SST and Australian Spring Rainfall

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ABSTRACT

The relationship between variations of Indo-Pacific sea surface temperatures (SSTs) and Australian springtime rainfall over the last 30 years is investigated with a focus on predictability of inter–El Niño variations of SST and associated rainfall anomalies. Based on observed data, the leading empirical orthogonal function (EOF) of Indo-Pacific SST represents mature El Niño conditions, while the second and fourth modes depict major east–west shifts of individual El Niño events. These higher-order EOFs of SST explain more rainfall variance in Australia, especially in the southeast, than does the El Niño mode. Furthermore, intense springtime droughts tend to be associated with peak warming in the central Pacific, as captured by EOFs 2 and 4, together with warming in the eastern Pacific as depicted by EOF1.

The ability to predict these inter–El Niño variations of SST and Australian rainfall is assessed with the Australian Bureau of Meteorology dynamical coupled model seasonal forecast system, the Predictive Ocean and Atmospheric Model for Australia (POAMA). A 10-member ensemble of 9-month hindcasts was generated for the period 1980–2006. For the September–November season, the leading 2 EOFs of SST are predictable with lead times of 3–6 months, while SST EOF4 is predictable out to a lead time of 1 month. The teleconnection between the leading EOFs of SST and Australian rainfall is also well depicted in the model. Based on this ability to predict major east–west variations of El Niño and the teleconnection to Australian rainfall, springtime rainfall over eastern Australia, and major drought events are predictable up to a season in advance.

1. Introduction

The El Niño–Southern Oscillation (ENSO) is the dominant driver of interannual variations of Australian rainfall during austral winter [June–August (JJA)] and spring [September–November (SON); McBride and Nicholls (1983); Nicholls (1989)]. Dry (wet) conditions, especially across eastern Australia, are typically associated with El Niño (La Niña) events. Strong persistence of ENSO from austral winter to spring and into summer provides the basis for skillful seasonal prediction of eastern Australian rainfall up to one season in advance (e.g., Drosdowsky and Chambers 2001).

Scrutiny of the Australian rainfall–ENSO relationship indicates that magnitude of the Australian rainfall anomaly is not simply a linear function of the strength of ENSO, as measured by the Southern Oscillation index (SOI) or the Niño-3 sea surface temperature (SST) index. For instance, Power et al. (2006) have pointed out that the strength of an El Niño event, as indicated by the magnitude of a negative anomaly of the SOI, is not a good indicator of the strength of Australian rainfall deficit. However, the magnitude of the positive SOI anomaly during La Niña is a good predictor of the strength of the increased rainfall anomaly. A plausible explanation for the lack of a simple linear relationship between rainfall deficit and El Niño strength is that each El Niño event has its own unique pattern of SST anomaly (e.g., Trenberth and Stepaniak 2001), and Australian climate is sensitive to these inter–El Niño variations of SST (Wang and Hendon 2007). In particular, below-average rainfall across Australia is more associated with El Niño events that have their maximum SST warming concentrated more in the central Pacific than in the eastern Pacific. Wang and Hendon (2007) showed that the massive 1997 El Niño, whose maximum SST warming occurred in the far eastern equatorial Pacific, produced a relatively
weak impact on Australian spring rainfall. By contrast, the relatively weak El Niño of 2002, as judged by the magnitude of the SST anomaly in the eastern equatorial Pacific (e.g., the Niño-3 index), resulted in a devastating drought due to the occurrence of a relatively strong positive SST anomaly just east of the date line.

This sensitivity of Australian rainfall to the detailed spatial structure of SST anomalies during El Niño hinders skillful prediction of Australian rainfall using schemes that depend primarily on the occurrence of ENSO (e.g., Troccoli et al. 2007). Skillful prediction of rainfall during each El Niño event may be feasible if the prominent features of the pattern of SST anomaly that are closely tied to Australian rainfall sensitivity are predictable. It is an outstanding question, therefore, whether the detailed pattern of SST anomaly in each El Niño event can be predicted. And, taking this question one step further, can the differences in the associated Australian rainfall anomalies then be predicted? The current study aims to address these questions, using an ocean–atmosphere coupled dynamical forecast system.

For this research, we utilize the Australian Bureau of Meteorology’s dynamical seasonal forecast system, the Predictive Ocean and Atmospheric Model for Australia (POAMA). The model and the verification datasets are described in section 2. In section 3 we review and further explore the observed relationship between Australian rainfall and tropical Indo-Pacific SST variability. In section 4 we assess the capability of the POAMA system to predict tropical Indo-Pacific SST and associated Australian rainfall beyond that simply related to the occurrence of ENSO. Finally, concluding remarks will be given in section 5.

2. POAMA seasonal forecast system

As a major effort to improve seasonal predictive skill for Australian climate, the Australian Bureau of Meteorology (BoM) and the Commonwealth Scientific and Industrial Research Organization (CSIRO) jointly developed a coupled ocean–atmosphere seasonal forecasting system, POAMA (Alves et al. 2003; more information available online at http://poama.bom.gov.au). The initial focus of POAMA was on the prediction of tropical SST anomalies associated with ENSO, for which POAMA has demonstrable skill for lead times of two–three seasons (Wang et al. 2008). The POAMA system has been run operationally since 2002, and it has been continuously upgraded in order to increase the capability of regional climate prediction in conjunction with improved ability to predict tropical SST variations.

The atmospheric component of the current version of POAMA (v1.5b) is the Bureau of Meteorology unified atmospheric model (BAM) version 3.0d (Colman et al. 2005; Wang et al. 2005), which is a spectral-transform model run with triangular truncation at wavenumber 47 (~300 km grid) and 17 vertical levels. The ocean component is the Australian Community Ocean Model version 2 (ACOM2; Schiller et al. 2002), which was developed from the Geophysical Fluid Dynamics Laboratory (GFDL) Modular Ocean Model version 2 (MOM2; Pacanowski 1996). The zonal resolution of the ocean model is 2°, and the meridional spacing is 0.5° within 8° of the equator, increasing gradually to 1.5° near the poles. There are 25 levels in the vertical, with 12 levels in the top 185 m. The ocean and atmosphere models are coupled every 3 h, using the Ocean Atmosphere Sea Ice Soil (OASIS) coupling software (Valcke et al. 2000) without flux correction. Further details of each component of the POAMA system can be found in Schiller et al. (2002), Alves et al. (2003), Zhang et al. (2006), and Zhao and Hendon (2009).

Forecasts from POAMA are initialized from observed atmospheric and oceanic states. The atmospheric initial conditions are provided by the Atmospheric–Land Initialisation (ALI) scheme (Hudson and Alves 2007). ALI creates a set of atmosphere–land initial states by nudging zonal and meridional winds, temperatures, and humidity from the atmospheric model of POAMA toward an observationally based analysis. ALI nudges to the re-analyses from the 40-yr European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-40; Uppala et al. 2005) for the earlier period of hindcasts (1980–2001) and toward the analyses from the BoM’s NWP system (GASP) for the later period of hindcasts (2002–06) and for the real-time forecasts. The resultant atmospheric fields are similar to the analyses of ERA-40/GASP, but the nudging scheme results in less initial shock than if the ERA-40/GASP analyses are used directly as initial conditions. The land surface conditions such as soil moisture and temperature are also initialized by being brought into balance with the atmospheric surface fields produced by ALI. Ocean initial conditions are generated through an ocean data assimilation scheme, using the optimum interpolation (OI) technique described by Smith et al. (1991). Ocean current increments are implemented by applying the geostrophic relation to the temperature increments following Burgess et al. (2002). Subsurface temperature data observed in the top 500 m are fed into the assimilation system. During the assimilation cycle, SST is strongly nudged to the observed SST analysis (Reynolds et al. 2002). The OI scheme is used to correct the ocean model background field every 3 days using a 3-day observation window.

For this study a 10-member ensemble of nine month hindcasts was generated each month for the period of
1980–2006. The ensemble was generated by perturbing
the atmospheric initial conditions by successively pick-
ing the analysis from a 6-h earlier period starting from
the first day of each month. There was no perturbation
applied to the ocean initial conditions.

Ensemble-mean hindcasts of Indo-Pacific SST, Aus-
tralian rainfall, and tropical-wide rainfall were verified
against the Hadley Centre Sea Ice and SST (HadISST)
data (1° × 1° resolution monthly data available online at
http://hadobs.metoffice.com/hadisst/data/download.html;
Rayner et al. 2003), the gridded Australian rainfall ana-
lyses produced by the National Climate Centre (Jones and
Weymouth 1997), and the Climate Prediction Center
(CPC) Merged Analysis of Precipitation global rainfall
analyses (Xie and Arkin 1997), respectively. Anomalies
of the verification data were formed by removal of the
monthly mean seasonal cycle for 1980–2006. Anomalies
of the hindcasts were formed relative to the forecast
model’s climatology for the same period, which is a
function of start month and lead time. In this fashion, the
mean bias of the model (discussed in more detail later)
is removed (e.g., Stockdale et al. 1998).

The climate of nonflux-corrected coupled seasonal
forecast models such as POAMA drifts as the forecast
progresses. A warm bias off the west coast of South
America and a tropical-wide cold bias develop imme-
diately and increase with lead time (Fig. 1). A cold
tongue bias in the equatorial Pacific also develops, ef-
effectively extending the cold tongue far into the western
Pacific as lead time increases. These model bias and
climate drift negatively impact the simulated/forecast
variability, especially that associated with ENSO. As
discussed in Zhao and Hendon (2009) and as will be
shown in section 4, a direct result of the cold tongue bias
in the equatorial Pacific is that the maximum ENSO
variability in SST shifts westward away from the South
American coast with increasing lead time. Such drift in
the SST variability associated with ENSO affects the

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**FIG. 1.** (a) Observed mean SST (HadISST) in SON and (b)–(d) the difference between POAMA predicted and observed SST as a function of lead time. Positive (negative) values mean that POAMA predicts higher (lower) SST than observations on average. The contour interval is 2°C in (a) and 0.5°C in (b)–(d). The domain is 30°S–20°N, 40°–280°E.
model’s ability to discern differences in SST patterns between ENSO events, especially at longer lead times. The negative impact of the model bias and drift on ENSO also affects the ENSO–rainfall teleconnection to Australia. While the mean climate bias is simply removed by forming model anomalies from the lead-time-dependent model climatology, removal of the bias in variability requires more sophisticated postprocessing techniques such as statistical calibration (e.g., Barnett et al. 1993; Mo and Straus 2002; Kug et al. 2008), which will be reported on elsewhere. Despite the 1°–2°C cold SST bias across much of the Indo-Pacific warm pool by the end of the 9-month forecast, the mean rainfall distribution remains relatively constant and realistic through the forecast (Fig. 2). However, rainfall over the maritime continents and the Bay of Bengal is underestimated in the model. Also, forecast rainfall is deficient over the Australian continent, but the pattern of rainfall is reasonably well represented (e.g., the maximum in the southeast during spring) and does not drastically change with lead time.

For the analyses that follow, rainfall anomalies from both model and verification are seasonally averaged. We limit our interest to the hindcasts that are verified in both model and verification are seasonally averaged. We limit our interest to the hindcasts that are verified in

3. Observed variability of tropical Indo-Pacific SST and its relationship with Australian rainfall

The dominant modes of variability of observed tropical Indo-Pacific SST are identified with empirical orthogonal function (EOF) analysis. We use the covariance matrix to determine the eigenvectors over the tropical domain of 30°S–20°N, 40°–280°E. Figure 3 displays the leading four EOFs of SST for the SON season in the period 1980–2006. These first four EOFs account for 83% of the observed variance in SON. The spatial patterns of the EOF modes are displayed as the regression of SST anomaly onto the principal component (PC) time series and are scaled for a one standard deviation anomaly of the PCs. The merit of presenting EOF patterns in this way is that the resultant regression patterns are consistent with the original EOF patterns, and they show the magnitude of the temperature change at each grid point associated with a one standard deviation anomaly in PCs (e.g., Thompson and Wallace 2000). Hereafter, we will refer to these regression patterns as the EOFs.

The spatial pattern of the first mode (EOF1; Fig. 3a) represents mature ENSO conditions (e.g., Bjerknes 1969; Trenberth 1997) and accounts for by far the largest amount of variance (61%). It is one signed in the equatorial eastern Pacific Ocean, and opposite signed but with much weaker loading in the western Pacific and the eastern Indian Oceans. Its standardized time series (PC1) has large positive loadings (≥1) in 1982, 1987, and 1997 and large negative loadings (≤−1) in 1988, 1998, and 1999, which are major El Niño and La Niña events, respectively. PC1 is highly correlated with the Niño-3 and Niño-3.4 indices (correlation coefficient, $r \sim 0.99$ and 0.98, respectively), which are widely used as ENSO indicators (e.g., Trenberth 1997).

EOF2 (Fig. 3b) represents a major east–west variation of ENSO (Trenberth and Stepaniak 2001; Hoerling and Kumar 2002; Kumar et al. 2005; Ashok et al. 2007; Wang and Hendon 2007). This mode has large loadings of opposite sign along the equator near the date line and off the coast of South America, and has been recognized as an important mode for capturing different characteristics and the evolution of each ENSO event (e.g., Trenberth and Stepaniak 2001; Ashok et al. 2007). For instance, the 1997 El Niño event is characterized by the maximum SST warming confined to the far eastern Pacific, which is described by strong negative loading of EOF2 together with strong positive loading on EOF1 (Wang and Hendon 2007). On the other hand, the westward-shifted El Niño events in the mid-1990s and early 2000s are associated with positive loading of EOF2 together with weak positive loading of EOF1. The variability of EOF2 in SON season is also captured by the trans-Niño index (Trenberth and Stepaniak 2001; $r \sim −0.94$) and the El Niño Modoki index (Ashok et al. 2007; $r \sim 0.92$).

EOF3, which explains 7% of the variance of tropical Indo-Pacific SST, appears to depict the recent warming trend in the Indo-Pacific basin (Fig. 3c). The linear trend accounts for about 60% of the SST variance explained by EOF3, and this trend in PC3 is statistically significant at the 99% confidence level (c.l.), using the Student’s $t$ test applied to the least squares fit slope (assuming $n − 2$ degrees of freedom, which is 25 in the present study). EOF4 also has its maximum loading in the equatorial central Pacific and also contributes to the east–west variations of El Niño (e.g., large positive loading during the westward-shifted 2002 El Niño event; Fig. 3d).

Last, it is of interest to note that EOF1 and EOF4 appear to include the Indian Ocean dipole patterns (e.g., Saji et al. 1999). During the spring season, variability of the Indian Ocean dipole Mode Index (DMI; $^1$ Saji et al. 1999) is highly correlated with PC1 ($r \sim 0.82$), which emphasizes the tight coupling of the Indian Ocean dipole with ENSO during the past 30 years. The correlation between the DMI and PC4 is only 0.33, but after the

\[ \text{DMI} = \text{SST}_{(50–70^\circ E,10^\circ S–10^\circ N)} - \text{SST}_{(90–110^\circ E,10^\circ S–0^\circ)}. \]

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$^1$ DMI = SST$_{(50–70^\circ E,10^\circ S–10^\circ N)} −$ SST$_{(90–110^\circ E,10^\circ S–0^\circ)}$. 

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removal of the linear relation of PC1 (i.e., removal of ENSO) from the DMI, the correlation between the DMI and PC4 increases to 0.58 (statistically significant at the 99% c.l., assuming 27 degrees of freedom—i.e., each year is independent).

The relationship of Australian regional rainfall with each EOF of tropical SST is demonstrated by the regression of gridded rainfall onto each of the four standardized PCs (Fig. 4). The ENSO mode represented by SST EOF1 accounts for a significant fraction of rainfall variability in the east, north, and southwest corner of the country with positive loading of EOF1 being associated with decreased rainfall. The influence of SST EOF2, which has a maximum loading over the date line, on
Australian rainfall is similar in magnitude to that of SST EOF1 and is concentrated over the northwest and the east. Positive amplitude of EOF2 is related to reduced rainfall in these regions. SST EOF3, which we have interpreted as capturing the recent warming trend of tropical SST, appears to contribute little to Australian rainfall in this season. SST EOF4, which in its positive phase is characterized by a positive SST anomaly over the equatorial central Pacific and a positive phase of the Indian Ocean dipole pattern (Saji et al. 1999) is associated with negative anomaly of rainfall over the southeastern part of the country and explains a similar amount of rainfall variance as EOF1 in that region. SST EOFs 2 and 4 account for 22%, 15%, and 6% of the variance of Australian area-mean rainfall, respectively. It is noteworthy that SST EOFs 2 and 4 together explain as much Australian-mean rainfall variance as that of SST EOF1, and across the east and south EOF2 and EOF4 account for more rainfall variance than EOF1.

The important role of the leading modes of tropical SST variability for Australian spring rainfall variations is also confirmed by the singular value decomposition (SVD) analysis (Bretherton et al. 1992) of Australian rainfall with tropical Indo-Pacific SST and by the EOF analysis on Australian rainfall (not shown). During the period analyzed here, EOFs 1, 2, and 4 of tropical Indo-Pacific SST displayed in Fig. 3 are consistent with the SST patterns of the first three modes of maximum covariability between the tropical SST and Australian rainfall. Also, the first EOF pattern of springtime rainfall (explaining 46% of the total Australian spring rainfall variance) is highly consistent with the pattern of rainfall depicted by the regression onto the ENSO mode shown in Fig. 4a (pattern correlation ~0.8). The second EOF of rainfall (explaining 13% of the total variance) shows very similar pattern to the regression of rainfall onto SST EOF4 (Fig. 4d; pattern correlation ~0.7). The PC time series of the rainfall EOF1 and EOF2 are correlated with PC1 and PC4 of tropical SST, respectively, at about 0.5. The influence of SST EOF2 seems split between rainfall EOF1 and EOF2. These additional analyses highlight the tight connection between Australian rainfall and the tropical Indo-Pacific SST variabilities in the spring season.

Having discussed the relationship of the tropical Indo-Pacific SST with Australian rainfall, it is an interesting question to address how much of Australian rainfall is explained by the Indian Ocean SST variability that is independent from Pacific Ocean SST variability. Nicholls (1989) and Simmonds and Rocha (1991) demonstrated that there is a significant relationship between Australian rainfall and Indian Ocean SST that is independent.
of ENSO in the winter season. However, in the spring season tropical Indian Ocean SST variability represented by the DMI is significantly related to that of ENSO during the last 30 years analyzed here, and therefore, the regression pattern of Australian rainfall onto the DMI (Fig. 5) is in high agreement with that onto ENSO (cf. Fig. 4a). To see the influence of the component of the Indian Ocean dipole pattern that is unrelated to ENSO on Australian spring rainfall, we calculate the part correlation between SST and DMI and between Australian rainfall and DMI when the association of DMI with SST PC1 (the ENSO mode) is first removed (Fig. 6). The part correlation is expressed as

\[ r_{y|x|z} = \frac{r_{y|x} - r_{y|z}r_{x|z}}{\sqrt{1 - r_{x|z}^2}}, \]

where \( y \) is a dependent variable (e.g., Australian rainfall), \( x \) is an independent variable (e.g., DMI), and \( z \) is an independent variable whose influence is removed from \( x \) (e.g., SST PC1). Figure 6a shows the ENSO-independent component of SST associated with the Indian Ocean dipole mode. Interestingly, the impact of the ENSO-free DMI variability on Australian rainfall turns out to be very small in the spring season (Fig. 6b).

In summary, tropical Indo-Pacific SST variability can account for the majority of Australian spring rainfall variations in the last three decades. SST EOFs 2 and 4 account for some important inter–El Niño variations of tropical Indo-Pacific SST, especially related to the east–west shifts.

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2 The correlation between a dependent variable and the residual of the prediction of one independent variable by the other variable(s) (also called semi-partial correlation; H. Abdi, W. J. Dowling, D. Valentin, B. Edelman, and M. Posamentier 2002, personal communication). This contrasts with the partial correlation, which removes the influence of the other variable(s) from both dependent and independent variables.
of El Niño anomalies in the Pacific for which Australian rainfall is sensitive. EOFs 2 and 4 together explain as much Australian rainfall variance as does EOF1 (the dominant ENSO mode). In the next section, we will assess the prediction skill of the dominant ENSO mode and the higher-order EOFs of the SST and their teleconnections with Australian rainfall.

4. Skill of POAMA hindcasts

a. Tropical SST and its teleconnection with Australian rainfall

Prior to assessing the skill of predicting the observed EOFs of SST, we first examine the intrinsic behavior of the POAMA forecast model for representing ENSO and the higher-order EOFs of SST. Figure 7 displays the first four EOF modes of predicted SST at lead time 0 month (i.e., forecasts initialized on 1 September for SON). The model’s first four EOFs explain 76% of the total variance of the predicted SST for the tropical Indo-Pacific domain. The first and second EOFs are very similar to their observed counterparts shown in Fig. 3, while the third and fourth EOFs are not. This is confirmed by the pattern correlation between predicted and observed EOFs: the correlation for EOF1 is 0.93 and for EOF2 is 0.80, but this falls to 0.51 for EOF3 and 0.22 for EOF4. Predicted EOF3 appears to stem from a combination of observed EOFs 3 and 4, having one sign of SST over the western Pacific and Indian Oceans and also a local maximum loading along the equator over the central Pacific. Predicted EOF3 is correlated with observed EOF4 as much as it is with observed EOF3 (correlation between predicted EOF3 and observed EOF4 is ~0.49). The ability to simulate the dominant patterns of SST associated with ENSO and the higher modes of SST variability seems adversely affected by the model bias and drift with increasing lead time (Zhao and Hendon 2009). As an example, the EOF patterns show the westward shift of the maximum SST loadings over the Pacific Ocean. Consequently, the pattern correlations of EOFs 1, 2, 3, and 4 between POAMA and their observed counterparts decrease to 0.88, 0.61, 0.25, and 0.05, respectively, by the 6-month lead time.

To assess the ability to predict the observed EOFs of tropical SST, we project POAMA SST predictions onto the observed EOF patterns shown in Fig. 3 and obtain the resultant loading time series. From now on, we will focus on EOFs 1, 2, and 4 because EOF3, which mainly represents the warming trend of the tropical ocean, has little influence on Australian rainfall in SON. Figure 8 demonstrates the skill for predicting observed EOFs 1, 2, and 4, using correlation and normalized root-mean-square-error (NRMSE; i.e., forecast rmse normalized by the standard deviation of the respective observed PC time series). The POAMA predictions readily beat persistence for all three PCs through all the lead times (LTs). Especially at short lead times (LTs of 0–1 month),
the phase and the amplitude of all three PCs are skillfully predicted \((r > 0.6\) and NRMSE < 1). Skill for predicting PC1 and PC2, as judged by \(r > 0.6\), extends to a 6-month lead time, whereas the forecast skill for PC4 drops off rapidly beyond one month lead. On the other hand, the normalized standard deviation of predicted PC2 and PC4 decreases substantially at lead times longer than 3 months, which indicates that predicted amplitude of PC2 and PC4 is much smaller than the amplitude of their observed counterparts at longer lead time. This reduction in amplitude is likely due to the model’s ENSO mode dominating the variance of SST at longer lead times. For instance, the predicted PC1 explains up to 80% of the tropical SST variance with lead times longer than 2 months. This dominance of EOF1 and weakening amplitude of EOFs 2 and 4 hinder the ability to discern the differences between eastward- and westward-shifted El Niño events at longer lead times. Finally, the warming trend in SST is captured in the predictions as evidenced by the correlation between the predicted and the observed time series of observed EOF3 \((r \sim 0.8\) at LT 0 and 0.6 at LT 6). However, persistence also offers a good prediction for EOF3, and the skill of the POAMA prediction is comparable to that of persistence.

To sum up, the POAMA forecast model is able to predict the occurrence of El Niño and La Niña (based on the ability to predict EOF1 of tropical SST) at lead times to 6 months and some important spatial details of tropical Indo-Pacific SST (represented by EOFs 2 and 4) at lead times of up to 2–3 months.

This leads us to ask whether this skill in predicting SST transfers to skillful predictions of rainfall over Australia. To answer this question, we first examine the teleconnection between tropical SST and Australian rainfall as simulated by the forecast model. The teleconnection is evaluated by the regression of the predicted Australian spring rainfall onto the predictions of the observed EOFs 1, 2, and 4 of SST (Fig. 9). The regression is scaled for a one standard deviation anomaly of each predicted PC. Overall, the observed relationship for EOFs 1, 2, and 4 is reasonably well represented at short lead times, but the realistic representation of the teleconnection degrades at longer lead times especially for EOF4. Compared to the observed relationships (Fig. 4), predicted rainfall is more strongly impacted by SST EOF2 (Fig. 9). This excessively strong relationship seems to result from model bias and drift that cause the region of maximum SST variability to be shifted westward of the observed counterpart from the start of the forecast and push it farther west with increasing lead times. Because Australian spring rainfall variability is most sensitive to SST variations over the central Pacific (Wang and Hendon 2007, their Fig. 6a), predicted rainfall is likely to respond strongly to the erroneously enhanced variability of SST in the central Pacific. Predicted SST PC2 explains about 50% of the predicted Australian-mean rainfall variance throughout the 9-month forecasts whereas the observed PC2 accounts for 15% of the observed Australian rainfall. Predicted SST PC4 is associated with similar amount and pattern of rainfall variation to that of PC2 at LT 0, probably because SST EOF4 also has its maximum loading over the central Pacific. However, the relationship between PC4 and rainfall diminishes at longer lead times as POAMA loses skill for predicting EOF4 beyond a 1-month lead. In contrast, the teleconnection between Australian rainfall and eastern Pacific SST (PC1) is significantly underestimated at lead time 0 (Fig. 9a), suggesting some kind of spinup problem.

At longer lead times, the relationship of rainfall with PC1 resembles that with PC2, which again seems to reflect the westward drift of the maximum SST variability in POAMA with increasing lead times. For instance, as a result of the mean-state drift, the maximum SST variability is placed over the central Pacific Ocean \((170°-130°W)\) at LT 3 months (not shown), and this SST variability projects onto both observed EOFs 1 and 2. Because the predicted
PCs obtained in this fashion are not orthogonal, the predicted PC1 and PC2 can explain similar patterns of the rainfall change.

In light of the observation that central Pacific SST variability is important for Australian rainfall, it is encouraging to see that this sensitivity is simulated in the predictions. Nevertheless, it is evident that the simulated rainfall teleconnection with tropical SST suffers from model bias and drift that will hamper, to some degree, skillful forecasts of rainfall.

b. Prediction of Australian spring rainfall

Prediction skill for rainfall from the POAMA hindcasts is assessed in terms of probabilistic forecasts for exceeding median rainfall, using individual ensemble members. Medians of seasonal rainfall are obtained from the hindcasts in a cross-validated fashion at each lead time. Figure 10 displays the $2 \times 2$ contingency table, and proportion correct, hit rate, and false alarm rate are derived from the table as follows:

\[
\text{proportion correct} = \frac{(a + d)}{(a + b + c + d)}, \tag{2}
\]

\[
\text{hit rate} = \frac{a}{(a + c)}, \quad \text{and} \tag{3}
\]

\[
\text{false alarm rate} = \frac{d}{(b + d)}, \tag{4}
\]
where $a$, $b$, $c$, and $d$ indicate the frequencies of four different types of forecast and observation pairs for a dichotomous event in the $2 \times 2$ contingency table. The proportion correct (Wilks 2005) of the predicted rainfall is shown in Fig. 11 for lead time 0 and 3 months. Proportion correct is defined as the ratio of the number of correct forecasts to the total number of forecasts for an event (e.g., above median rainfall). For reference, we also show the proportion correct of the current operational seasonal forecast scheme implemented in the National Climate Centre (NCC) model. The NCC model is a statistical model based on the historical lead–lag relationship between two leading modes of tropical Indian and Pacific SST and Australian rainfall variations with 1 month lead time. Further details of this model can be found in Drosdowsky and Chambers (2001).

Figure 11 indicates that forecasts from POAMA for above-median rainfall are highly skillful over southeastern Australia (proportion correct $> 70\%$) and better than a climatological forecast (i.e., 50\%) over most of the country at LT 0. Forecast skill decreases with longer lead times, but POAMA predictions still perform better than the climatological forecast over the southeast with up to a 3-month lead time (Fig. 11b). The areas where rainfall is skillfully predicted are consistent with the areas where the teleconnection between rainfall and the leading modes of tropical SST is strong (cf. Fig. 9).

It is noteworthy that POAMA outperforms the NCC model for the period 1980–2006 over the southern half of the country (Fig. 11c). Marginal skill in the NCC statistical model in the southern part of Australia partly reflects that the internal dynamics in the atmosphere (especially, the southern annular mode and other low-frequency synoptic variability) play an important role in determining seasonal climate in the south (e.g., Hendon et al. 2007; Hope et al. 2009; Risbey et al. 2009). Although these internal dynamics limit the skill of POAMA prediction as well, POAMA forecasts derive some skill
from atmospheric initial conditions for the first month of prediction and also at longer lead times through more realistic evolution of tropical SST that has interacted with more realistic initial conditions (Lim et al. 2008; Hudson et al. 2009, manuscript submitted to Climate Dyn.). The NCC model, however, has better skill than POAMA in predicting above-median rainfall over parts of northern Australia in SON when the ENSO signal is strong (Fig. 4).

We also analyze the POAMA forecasts for above median rainfall, using the relative operating characteristics (ROC) diagram (Fig. 12; Mason and Graham 1999; Wilks 2005). All 27 years of hindcasts at all the grid points over Australia are used to draw the ROC curve at different lead times. A ROC curve is constructed by computing the hit rate and the false alarm rate [Eqs. (3) and (4)] of forecasts for an event (e.g., exceeding median rainfall), using increasing probability thresholds (from 0 to 1 with 0.1 interval in this study) to make forecast decisions for the yes or no in the $2 \times 2$ contingency table. The ROC curve of a perfect forecast system would have one point at the top-left corner as the hit rate $= 1$ and the false alarm rate $= 0$, and the ROC curve of the climatological forecast lies on the no skill line where the hit rate is equal to the false alarm rate regardless of the probabilistic thresholds. Figure 12 suggests that POAMA forecasts are able to discriminate the occurrence of above-median rainfall from its nonoccurrence by demonstrating higher hit rates than false alarm rates with any probability thresholds with the lead times of up to 3 months. However, the ROC curves are not very far from the diagonal line. Also, the ROC diagrams indicate that POAMA offers a wide range of probability for above-median rainfall, and the forecast outcomes are different depending on different probability thresholds, which indicates good resolution in POAMA forecasts. Again, the NCC operational statistical model shows very similar forecast features to the climatological forecast in its overall performance (Fig. 12c).

c. Major drought events

Wang and Hendon (2007) showed that the occurrence of Australian spring drought is sensitive to anomalous warming of the central Pacific Ocean. Their results are confirmed by examining Australia’s most severe droughts (standardized Australian area-mean rainfall $\leq -1$) over the last 30 years. The standardized amplitudes of SST EOFs 1, 2, and 4 and rainfall anomaly in the selected 7 driest years (1980, 1982, 1990, 1991, 1994, 2002, and 2006) are displayed in Fig. 13a. It is of interest to note that all seven droughts were associated with a warm SST anomaly over the central Pacific as captured by SST EOF2 and EOF4, but not all droughts occurred with typical El Niño conditions as indicated by positive loading on SST EOF1.
However, the latest four severe droughts occurred with positive amplitudes of all three EOFs of SST. The occurrence of these spring droughts and the associated patterns of SST are reasonably well predicted by POAMA at LT 0, as evidenced by correct signs of the ensemble mean predicted rainfall and SST PCs in most of the selected years (Fig. 13b). The model is seen to perform better in predicting the detailed features of SST and Australian rainfall deficits for more recent drought events. These droughts can be foreseen up to 3 months in advance even with no skill to predict PC4 (likely due to EOF2 dominantly impacting Australian rainfall in the model). However, the POAMA model tends to underestimate the magnitudes of drought.

5. Concluding remarks

In this study we have reexamined the relationship between tropical Indo-Pacific SST and Australian rainfall and assessed the capability of a dynamical seasonal prediction system, POAMA, to predict the inter–El Niño variations of tropical SST and associated Australian rainfall in austral spring.

About a half of Australian spring rainfall variability is explained by three leading EOF modes (EOFs 1, 2, and 4) of tropical Indo-Pacific SST for the period 1980–2006. The first EOF mode depicts canonical mature ENSO conditions with maximum loading over the equatorial eastern Pacific. The second and fourth EOF modes account for important east–west shifts of ENSO events with maximum loadings over the central Pacific. Our analysis has shown that EOF2 and EOF4 accounts for as much Australian rainfall variance as EOF1. Furthermore, the occurrence of a warm anomaly in the central Pacific as captured by EOF2 and EOF4 seems to explain some of the extreme spring rainfall deficits over Australia, which confirms the findings of Wang and Hendon (2007). Therefore, predicting Australian rainfall would appear to depend as much on the ability to predict the inter–El Niño variations of SST depicted by EOF2 and EOF4 as on the ability to predict mature El Niño conditions (EOF1 of SST).

The ability to predict these EOFs of SST has been explored with the POAMA forecast model. Observed EOF1 and EOF2 of tropical SST can be skillfully predicted with lead times of up to 6 months whereas observed SST EOF4 is predictable to a lead time of 1 month. The forecast model also realistically simulates the teleconnection between the predicted EOFs of SST and Australian rainfall at least a season in advance. This implies that POAMA forecasts have great value for anticipating the different flavored El Niños and the associated Australian climate response at least at short lead times. For instance, POAMA was able to predict extreme dry conditions over Australia with up to a 3-month lead time during some recent El Niño events whose maximum SST warming occurred far westward of the eastern Pacific. In general, POAMA provides more skillful rainfall forecasts over southeastern Australia than the climatological forecast and the statistical model used as the operating seasonal forecast system in the Australian Bureau of Meteorology.

However, model bias and drift appear to hamper skillful prediction of inter–El Niño variations at longer lead times because maximum SST variability is systematically shifted westward from the eastern Pacific basin. The teleconnection between tropical SST and Australian rainfall is also negatively affected by these spurious features, which inevitably limits the ability of POAMA to predict Australian rainfall variability despite the ability to skillfully predict tropical SST at much longer lead times. Therefore, further efforts should be pursued to reduce the model bias and drift. Also, regional climate variations can be better resolved by increased horizontal resolution and improved initial conditions (e.g., Kanamitsu et al. 2002; Doblas-Reyes et al. 2006;
On a more fundamental level, we should also seek improved understanding of the mechanisms that give rise to the east–west shifts of SST anomaly during El Niño events, which are critical for the prediction of Australian rainfall.

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