

## Forecasts of Near-Global Sea Surface Temperatures Using Canonical Correlation Analysis

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(Manuscript received 23 March 2000, in final form 23 February 2001)

### ABSTRACT

The skill of global-scale sea surface temperature forecasts using a statistically based linear forecasting technique is investigated. Canonical variates are used to make monthly sea surface temperature anomaly forecasts using evolutionary and steady-state features of antecedent sea surface temperatures as predictors. Levels of forecast skill are investigated over several months' lead time by comparing the model performance with a simple forecast strategy involving the persistence of sea surface temperature anomalies. Forecast skill is investigated over an independent test period of 18 yr (1982/83–1999/2000), for which the model training period was updated after every 3 yr. Forecasts for the equatorial Pacific Ocean are a significant improvement over a strategy of random guessing, and outscore forecasts of persisted anomalies beyond lead times of about one season during the development stages of the El Niño–Southern Oscillation phenomenon, but only outscore forecasts of persisted anomalies beyond 6 months' lead time during its most intense phase. Model predictions of the tropical Indian Ocean outscore persistence during the second half of the boreal winter, that is, from about December or January, with maximum skill during the March–May spring season, but poor skill during the autumn months from September to November. Some loss in predictability of the equatorial Pacific and Indian Oceans is evident during the early and mid-1990s, but forecasts appear to have improved in the last few years. The tropical Atlantic Ocean forecast skill has generally been poor. There is little evidence of forecast skill over the midlatitudes in any of the oceans. However, during the spring months significant skill has been found over the Indian Ocean as far south as 20°S and over the southern North Atlantic as far north as 30°N, both of which outscore persistence beyond a lead time of less than about one season.

### 1. Introduction

A number of models have been developed for making extended-range forecasts of sea surface temperature anomalies of the equatorial Pacific Ocean over lead times of several seasons (e.g., Barnett 1984; Zebiak and Cane 1987; Kirtman and Schopf 1998; Barnston and Ropelewski 1992; Ji et al. 1996; Anderson and Davey 1998; Stockdale et al. 1998; Tangang et al. 1998; Burgers 1999). The equatorial Pacific Ocean has been targeted by modelers because of its importance to interseasonal climate variability worldwide (Moura et al. 1992; Glantz 1994; Moura 1994; National Research Council 1996; Moura and Sarachik 1997). Predicting the inter- and intraseasonal variability of ocean areas other than the tropical Pacific has enjoyed attention only

recently, yet there is a need for global sea surface temperature forecasts for initializing the boundary conditions of atmospheric general circulation models in two-tiered forecasting approaches (Hunt et al. 1994; Goddard and Graham 1999; Mason et al. 1999). In addition, in many areas of Africa and South America, for example, climate variability is significantly affected by ocean areas other than the equatorial Pacific (Semazzi et al. 1988; Ward and Folland 1991; Lamb and Pepler 1992; Mason 1995; Moron et al. 1995; Tennant 1996; Kane 1997, 1999; Mason and Jury 1997; Rocha and Simmonds 1997; Enfield 1996; Janicot et al. 1998; Ward 1998; Fontaine et al. 1999; Landman and Mason 1999; Mason and Tyson 2000; Nobre and Cavalcanti 1999). There is thus a need for an a priori indication of the expected seasonal variability of ocean areas outside the equatorial Pacific. For short-range climate predictions, persisted sea surface temperature anomalies can be used effectively, but for longer lead climate forecasts, evolving temperatures should be predicted (Goddard and Graham 1997).

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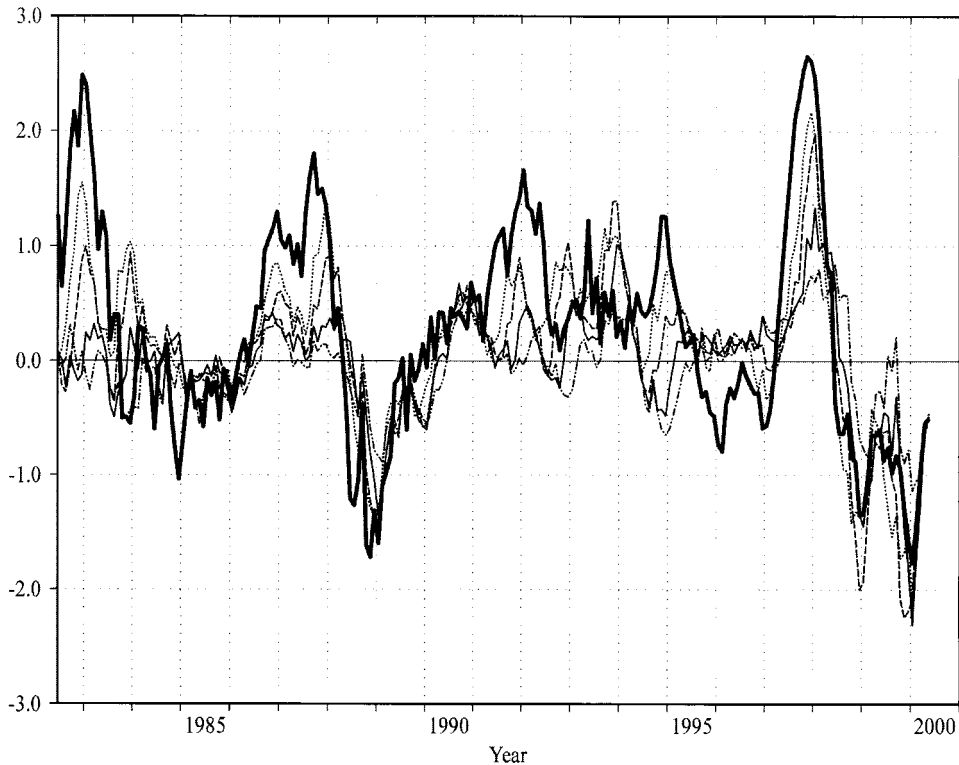


FIG. 1. Retroactive 0-month (dotted line), 3-month (dashed line), 6-month (thin solid line), and 9-month (dashed-dotted line) lead time forecast vs observed (thick solid line) sea surface temperature anomalies ( $^{\circ}\text{C}$ ) in the eastern equatorial Pacific Ocean for Jun 1982–May 2000.

Skill levels of extended range forecasts of equatorial Pacific sea surface temperature anomalies outscore forecasts of persisted anomalies, and are regarded as useful (Barnston et al. 1994). However, prediction skill is dependent on the phase of the ENSO cycle (Penland and Sardeshmukh 1995): most predictive skill derives largely from the recognition of the evolution of events already in progress, and not so much in recognition of times of ENSO phase changes (Barnston and Ropelewski 1992; Barnston et al. 1999). A fast decline in forecast skill is expected to be common with all ENSO forecast models because of the low variance found during the boreal spring months (Xue et al. 1994). However, this so-called spring barrier may not be intrinsic to the real climate system (Chen et al. 1995). In spite of the problems associated with ENSO forecasts, relationships between model skill and the spread of an ensemble of forecasts may provide useful indications of forecast confidence (Moore and Kleeman 1998).

There is evidence that the predictability of ENSO events varies interdecadally (Trenberth and Hurrell 1994). Despite the success of the forecasts of the 1982/83 warm event (Barnett 1984), models that rely on the delayed-oscillator-type behavior for their predictive skill (Mantua and Battisti 1994; Clarke and Li 1995; Suarez and Schopf 1988; Burgers 1999) were not particularly successful in predicting the warm

events of the boreal spring of 1993 and 1994/95 (Goddard and Graham 1997). Additionally, none of the models predicted the strength of the 1997/98 El Niño until the event was already becoming strong (Barnston et al. 1999; Landsea and Knaff 2000). The short-lived events during the first half of the 1990s may represent a different behavior of the coupled ocean–atmosphere system on intraseasonal timescales (Goddard and Graham 1999). It appears that the Southern Oscillation was damped during the 1990s in contrast with the self-sustaining Southern Oscillation during the 1980s (Philander 1998), but the exact reasons for the loss of predictability of ENSO events in the 1990s are still unknown. The skill levels developed for predicting the higher-amplitude interannual sea surface temperature variability of the 1980s are probably not relevant for the 1990s, and lead times of skillful forecasts for these short-lived episodes will probably be only a few months (Ming et al. 1996; Goddard et al. 2001).

A few modeling efforts have been directed at the equatorial Indian Ocean (Penland and Sardeshmukh 1995; Landman 1997; Mason et al. 1999), the equatorial Atlantic Ocean (Zebiak 1993; Penland and Matrosova 1998; Pezzi et al. 1998), and for setting up a multicentury sequence of global sea surface temperature fields (Navarra et al. 1998), but greater attention to the need for global forecasts is required. In this paper, the pre-

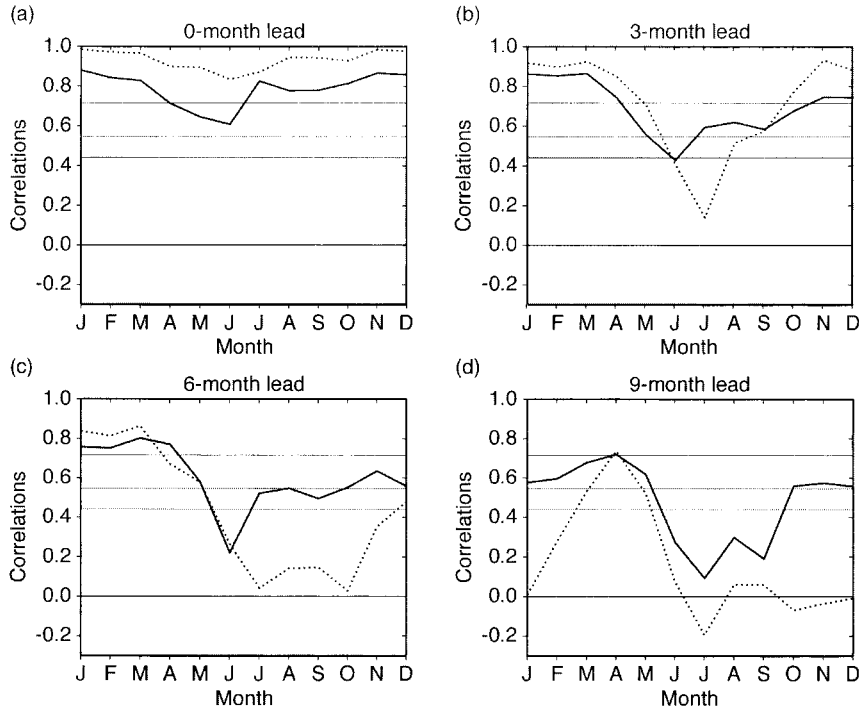


FIG. 2. Correlations between predicted and observed (solid line) and persisted and observed (dashed line) eastern equatorial Pacific Ocean sea surface temperature anomalies over the 18-yr independent period 1982/83–1999/2000 at (a) 0-month, (b) 3-month, (c) 6-month, and (d) 9-month lead times. The horizontal lines indicate the 90%, 95%, and 99% confidence levels.

dictive skill of a linear statistical model for forecasting near-global sea surface temperature forecasts is investigated over an 18-yr independent retroactive period from 1982/83 to 1999/2000 by comparing forecasts with observations and persisted sea surface temperature anomalies. The predictors are evolutionary features of

global sea surface temperatures predicting single-month sea surface temperatures for up to 11 months ahead. The model currently is being used at the South African Weather Bureau to issue near-global sea surface temperature forecasts operationally. These forecast temperatures serve as boundary forcing for an atmospheric general circulation model to produce seasonal rainfall forecasts in a two-tiered forecasting procedure (Landman et al. 2001).

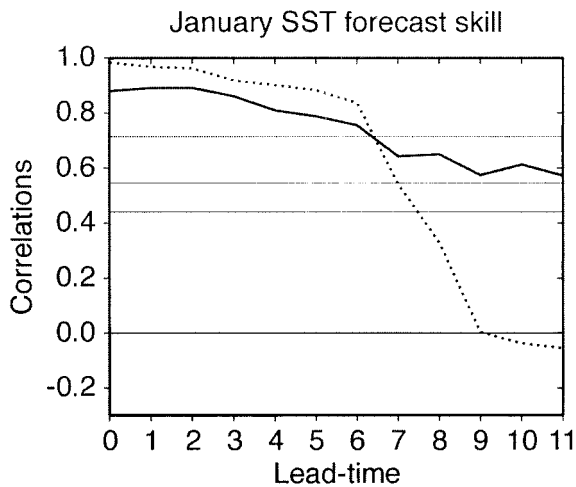


FIG. 3. Correlations between predicted and observed Jan eastern equatorial Pacific Ocean sea surface temperature anomalies (solid line) and between persistence and observed Jan anomalies (dashed line) over lead times from 0 to 11 months.

**2. Data and methods**

*a. Sea surface temperature data*

Reconstructed monthly sea surface temperature fields using empirical orthogonal functions (Smith et al. 1996) are available for the period 1950–95, and optimum interpolation (OI) sea surface temperature data (Reynolds and Smith 1994) were obtained for 1996–2000. During operational predictions, the latest OI data are used to update the sea surface temperature dataset. Both the reconstructed ( $2^\circ \text{ lat} \times 2^\circ \text{ long}$ ) and the OI ( $1^\circ \text{ lat} \times 1^\circ \text{ long}$ ) sets were reduced to a  $6^\circ \text{ latitude} \times 4^\circ \text{ longitude}$  grid. The data were reinterpolated to this coarser resolution to reduce the dimensionality of the eigenvalue problem of the EOF analysis used to reduce the data, while maintaining adequate representation of large oceanic features such as El Niño or La Niña.

### b. Sea surface temperature forecast model

A canonical correlation analysis (CCA) model was used to predict the near-global sea surface temperature anomalies. Four 3-month mean near-global sea surface temperatures were combined and used as predictors. Twelve subsequent 1-month near-global sea surface temperatures were the predictands. Preorthogonalization using standard EOF analysis (Barnston 1994) was performed on the predictor and the predictand field because of the large number of highly correlated variables and few observations contained in these fields. The predictor and predictand datasets were first standardized, so that the EOF preorthogonalization was performed using the correlation matrices. The number of EOF modes to be retained in the CCA eigenanalysis was determined such that about 60% of the variance of both the predictand and predictor field are explained. This value of 60% is justified because 70% is the recommended threshold by

the Guttman–Kaiser criterion (Jackson 1991), which normally overselects the number of modes, and Jolliffe (1972) suggested a fraction of the number of modes suggested by this criterion. The truncation for the number of CCA modes retained was determined by using the Guttman–Kaiser criterion. The predictand fields, which are a combination of several 1-month fields, were separated after the prediction to obtain forecasts for each 1-month period contained in the combined predictand field.

### c. Forecast lead times

In forecasting sea surface temperatures for each of 12 consecutive months, 12 lead times were considered as illustrated schematically for predicting the sea surface temperatures of 1982/83:

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S1:	<u>(J F M A M J J A S O N D)</u> <sub>1981</sub>	⇒	(j f m a m j j a s o n d) <sub>1982</sub>
S2:	<u>(F M A M J J A S O)</u> <sub>1981</sub>	⇒	(f m a m j j a s o n d) <sub>1982</sub> (j) <sub>1983</sub>
S3:	<u>(M A M J J A S O N)</u> <sub>1981</sub>	⇒	(m a m j j a s o n d) <sub>1982</sub> (j f) <sub>1983</sub>
S4:	<u>(A M J J A S O N D)</u> <sub>1981</sub>	⇒	(a m j j a s o n d) <sub>1982</sub> (j f m) <sub>1983</sub>
	⋮        ⋮        ⋮        ⋮        ⋮        ⋮        ⋮		
S10:	<u>(O N D)</u> <sub>1981</sub>	⇒	(o n d) <sub>1982</sub> (j f m a m j j a s) <sub>1983</sub>
S11:	<u>(N D J)</u> <sub>1981/82</sub>	⇒	(n d) <sub>1982</sub> (j f m a m j j a s o) <sub>1983</sub>
S12:	<u>(D J F)</u> <sub>1981/82</sub>	⇒	(d) <sub>1982</sub> (j f m a m j j a s o n) <sub>1983</sub>

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To demonstrate the definition of the lead times used in this paper, the prediction of January sea surface temperature anomalies are considered. For the predictor/predictand setup of S12, the lead time for January is defined as 1 month, for S11 the lead time is 2 months, and for S10 3 months. The January lead time for S1 is considered to be a zero-month lead time.

Forecasts have been produced for the 18-yr retroactive period of 1982/83–1999/2000. For the independent retroactive test period, the training period was expanded after predicting sea surface temperature anomalies for three subsequent and consecutive years, that is, for a training period of 30 yr for S12 (1951/52–1980/81), January sea surface temperature predictions were made for 1983–85, and for a training period of 33 yr (1951/52–1983/84) the forecasts were made for 1986–88. The process was continued until a 45-yr training period was used to make January sea surface temperature predic-

tions for 1998–2000. Similarly, forecasts were produced for the other 11 months.

### d. Significance tests

The threshold correlation values for the 90%, 95%, and 99% confidence levels are calculated by assuming that the degrees of freedom are equal for all the ocean basins considered here, and are based only on the number of years in the retroactive sample (18). However, in the presence of interannual autocorrelation associated with a warming trend, most notably in the equatorial Indian Ocean (Kawamura 1994), the effective degrees of freedom would be decreased and the correlation thresholds raised. Notwithstanding, the autocorrelation for the equatorial Indian Ocean calculated for the months of January, April, July, and October (the middle months of the four climatological seasons) over the 18-yr retroactive period was negligible. For the four months

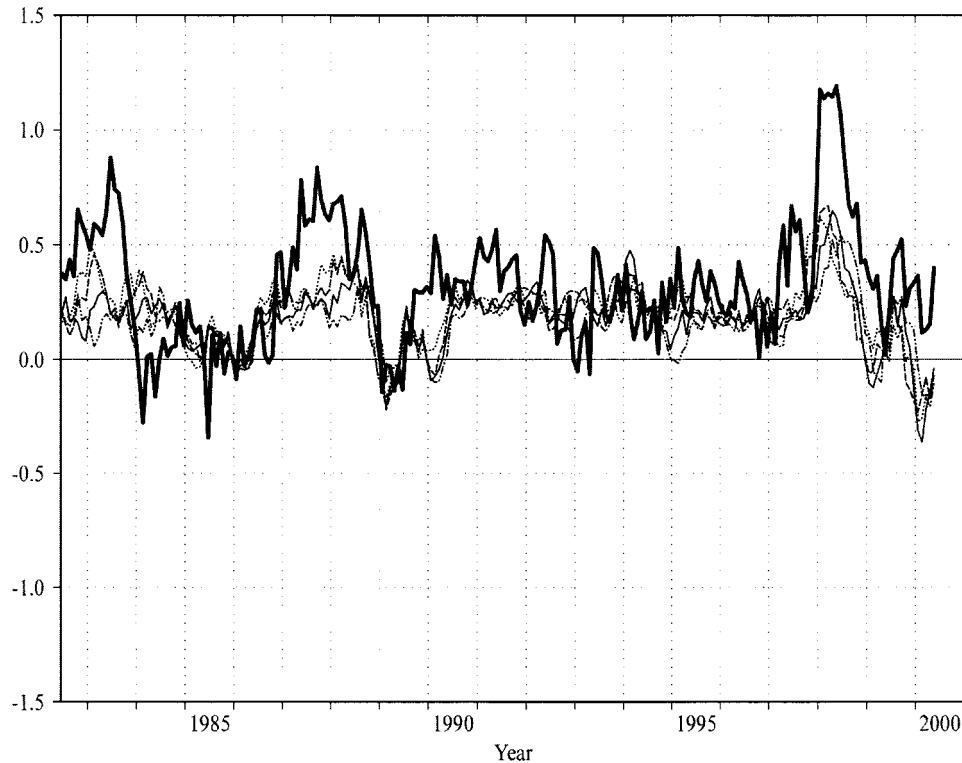


FIG. 4. Retroactive 0-month (dotted line), 3-month (dashed line), 6-month (thin solid line), and 9-month (dashed-dotted line) lead time forecast vs observed (thick solid line) sea surface temperature anomalies ( $^{\circ}\text{C}$ ) in the equatorial Indian Ocean for Jun 1982–May 2000.

and the three oceans considered, none of autocorrelations exceeded 0.15, with only two autocorrelation values larger than 0.1. The lack of significant autocorrelation in the equatorial ocean regions for the retroactive period despite the positive trend in temperatures is largely a result of the abruptness of warming that occurred in the late 1970s without much additional trend after the large shift. As a result, no adjustment has been made for autocorrelation when calculating the threshold correlation values for the various confidence levels.

### 3. Forecasts of equatorial sea surface temperatures

The model's ability to produce skillful predictions of near-equatorial sea surface temperature anomalies was first assessed for the equatorial oceans where useful skill has been demonstrated by a large array of different forecast models (see Barnston et al. 1994). Indices were calculated for each of the central equatorial Pacific Ocean (representing approximately the Niño-3.4 region), and the basins of the equatorial Indian Ocean ( $6^{\circ}\text{N}$ – $6^{\circ}\text{S}$ ,  $48^{\circ}$ – $104^{\circ}\text{E}$ ) and Atlantic Ocean ( $6^{\circ}\text{N}$ – $6^{\circ}\text{S}$ ,  $40^{\circ}\text{W}$ – $8^{\circ}\text{E}$ ). The assessment of the skill of the predictions of these area-averaged sea surface temperature indices was made for a retroactive forecast period from 1982/83 to 1999/2000. This 18-yr period exceeds the minimum of 10 yr of real-time forecasts that are needed

before an accurate estimate of operational forecast quality can be made (Barnston et al. 1994), and so the results presented in this paper should give a reliable indication of the operational skill of the model. Model forecast skill was compared with the skill that would be obtained using persisted sea surface temperature anomalies as a forecast.

#### a. Eastern equatorial Pacific Ocean

Retroactive forecast values, expressed in degrees Celsius, for each individual month of an 18-yr period commencing in June 1982–May 2000 for the eastern equatorial Pacific Ocean index at 0-, 3-, 6-, and 9-month lead times are shown in Fig. 1. The temporal correlations between the observed and predicted indices over the  $18 \times 12$  months are 0.82, 0.72, 0.61, and 0.51 for the four respective lead times. Most of the El Niño episodes were forecast successfully, although the strength of the events during the first half of the 1990s was not accurately predicted, as is the case for most other models (Barnston et al. 1994; Mason 1997; Goddard and Graham 1997; Philander 1998; Barnston et al. 1999). In addition, the model did not predict the strength of the 1982/83 El Niño event accurately. Similarly, the very strong El Niño event of 1997/98 was correctly predicted but with decreasing amplitude with increasing lead time: the pre-

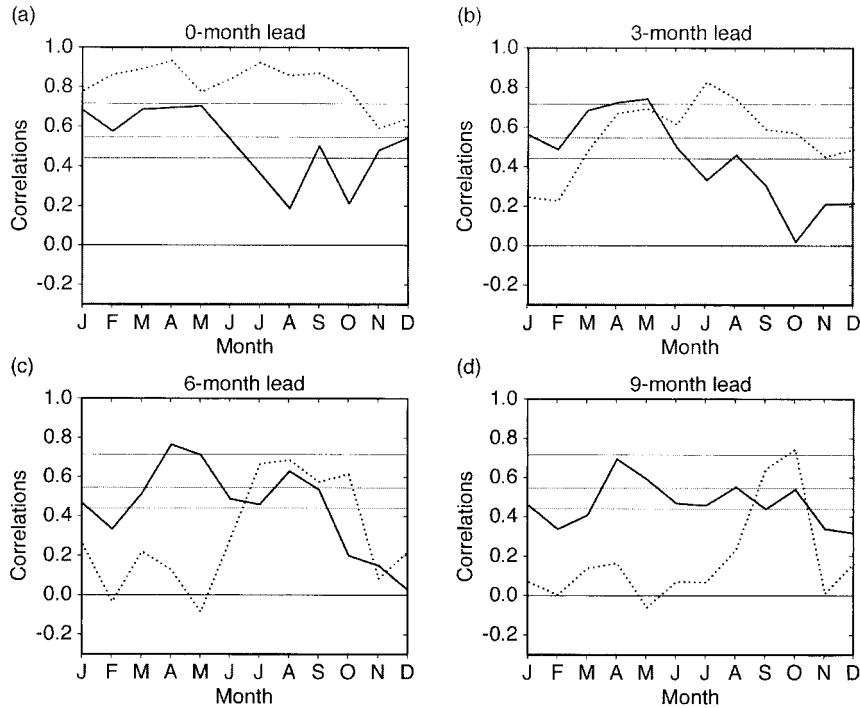


FIG. 5. Correlations between predicted and observed (solid line) and persisted and observed (dashed line) equatorial Indian Ocean sea surface temperature anomalies over the 18-yr independent period 1982/83–1999/2000 at (a) 0-month, (b) 3-month, (c) 6-month, and (d) 9-month lead times. The horizontal lines indicate the 90%, 95%, and 99% confidence levels.

dicted anomaly at 3-month lead time was more than twice as large as at the 9-month lead time.

The La Niña episodes were equally successfully predicted, although the strength of the anomalies was slightly overestimated for the two cold events that followed the strong 1997/98 El Niño event. Although the poor performance of the model during the early 1990s

is immediately apparent, the forecasts improved substantially toward the end of the decade when the occurrence of the El Niño event of 1997/98 and the subsequent two La Niña events of 1998/99 and 1999/2000 were predicted successfully. Although the 1997/98 El Niño event was predicted accurately, Fig. 1 gives the impression that the amplitudes of both the predicted and observed indices are considerably less than the generally reported anomaly of eastern equatorial Pacific Ocean of close to 4°C. The seemingly smaller amplitude in this paper is a consequence of the coarse grid being used, and because the Niño-3.4 region lies partly westward of region that experienced the maximum anomalies.

Figure 2 shows the annual cycle of correlations between the observed and predicted, and the observed and persisted sea surface temperature anomalies at 0-, 3-, 6-, and 9-month lead times as obtained over the retroactive period of 18 yr. A similar annual cycle in forecast skill has been found elsewhere using a CCA prediction model (Barnston and Ropelewski 1992), albeit for seasons as opposed to months. The forecasts of sea surface temperature of the eastern equatorial Pacific Ocean for the individual months of January–May are statistically significant at the 95% level of confidence for all the lead times in the figure. For this time of the year, the forecasts of persisted anomalies are even slightly more skillful than the model forecasts with lead times less than about 6 months. For other models, persistence forecasts for the equatorial Pacific usually are

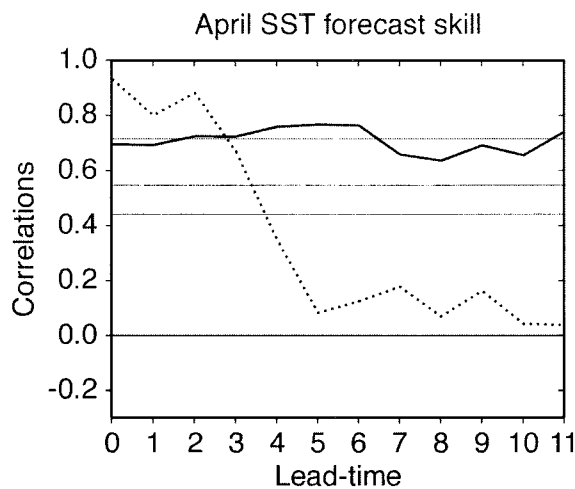


FIG. 6. Correlations between predicted and observed Apr equatorial Indian Ocean sea surface temperature anomalies (solid line) and between persistence and observed Apr anomalies (dashed line) over lead times from 0 to 11 months.



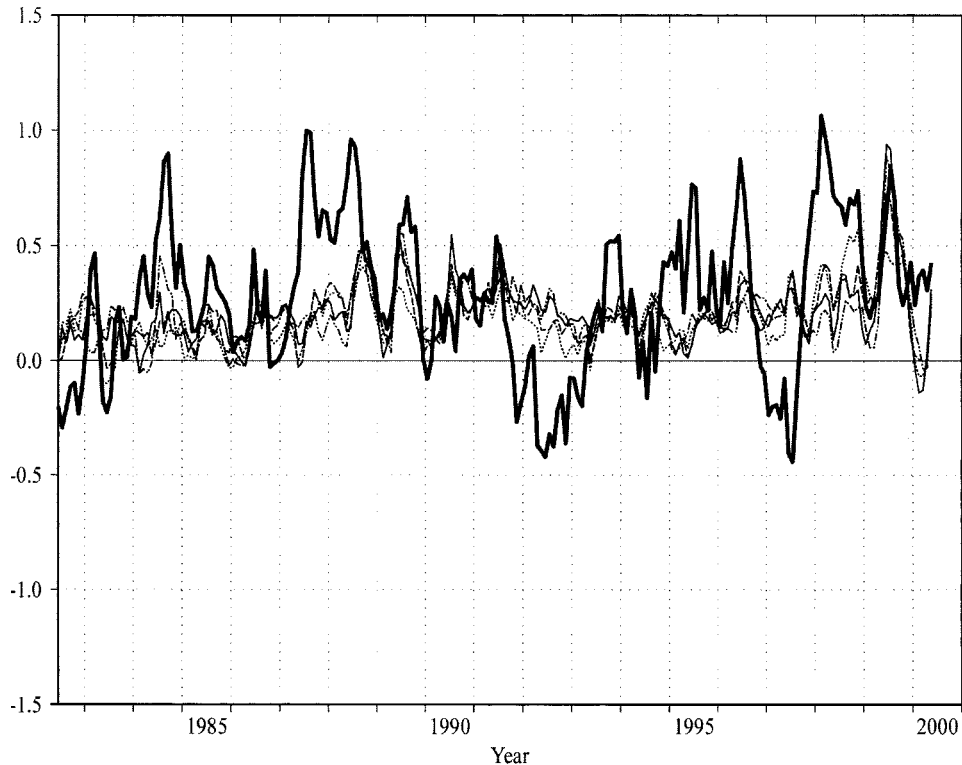


FIG. 7. Retroactive 0-month (dotted line), 3-month (dashed line), 6-month (thin solid line), and 9-month (dashed-dotted line) lead time forecast vs observed (thick solid line) sea surface temperature anomalies ( $^{\circ}\text{C}$ ) in the equatorial Atlantic Ocean for Jun 1982–May 2000.

similarly outscored only with lead times exceeding 6 months (Barnston et al. 1994).

Figure 3 emphasizes the superiority of the model forecasts at the longer lead times. The figure shows the decrease in skill in forecasting January sea surface temperatures at increasing lead times. For persistence, skill drops off rapidly beyond lead times of 6 months, while the model skill decreased only gradually with increasing lead time and subsequently outscored the persistence forecast skill after 6 months. During the development phase of ENSO (Jun–Oct) the model forecasts are more skillful than persistence beyond only about a one-season lead period (Fig. 2).

#### b. Equatorial Indian Ocean

Retroactive forecast values, again expressed in degrees Celsius, for each individual month of the 18-yr period commencing in June 1982 for the equatorial Indian Ocean index at the four respective lead times considered are shown in Fig. 4. The temporal correlations between the observed and predicted indices are slightly less than 0.5 over the  $18 \times 12$  months for the 0-, 3-, 6-, and 9-month lead times. The variance of the observed and forecast anomalies is considerably less than for the Pacific Ocean, and although the retroactive correlations are lower than those for the eastern equatorial

Pacific Ocean, they are still statistically significant at the 99% level of confidence. As for the equatorial Pacific Ocean, most of the warm and cold events were forecast successfully. However, the amplitudes of the major events are not captured accurately, which is particularly evident during the 1997/98 El Niño event even though a record warming was anticipated. The model predicted the subsequent cooling trend over the next 2 years correctly, but incorrectly predicted negative anomalies during this period. The model predictions for the 1988/89 Indian Ocean cold event were more accurate. Additionally, the model predicted the anomalously high equatorial Indian Ocean sea surface temperatures that have been persisting since the mid-1970s when a large positive shift in sea surface temperatures occurred (Kawamura 1994) without any significant additional warming thereafter. The success of the model in predicting this warm bias is not reflected in the correlation coefficients used to measure forecast skill.

Figure 5 shows the annual cycle of correlations between the observed and predicted, and the observed and persisted Indian Ocean sea surface temperature anomalies at 0-, 3-, 6-, and 9-month lead times as obtained over the retroactive period of 18 yr. The correlations of Fig. 5, while suggesting a lower level of skill for the prediction of equatorial Indian Ocean sea surface temperatures compared with the skill for the equatorial Pa-

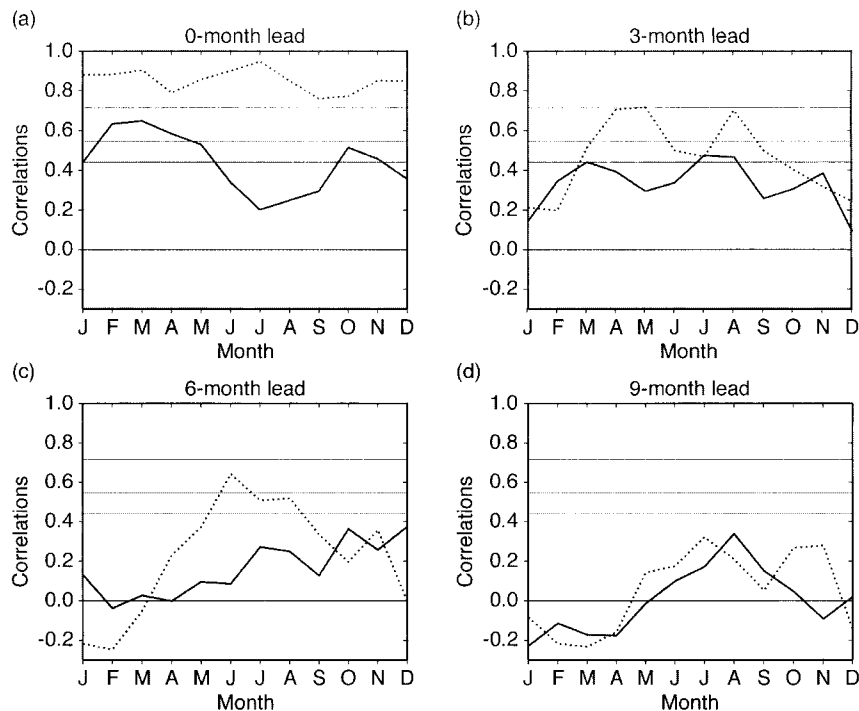


FIG. 8. Correlations between predicted and observed (solid line) and persisted and observed (dashed line) equatorial Atlantic Ocean sea surface temperature anomalies over the 18-yr independent period 1982/83–1999/2000 at (a) 0-month, (b) 3-month, (c) 6-month, and (d) 9-month lead times. The horizontal lines indicate the 90%, 95%, and 99% confidence levels.

cific Ocean (Fig. 2), are consistently positive at all lead times, most notably for March–May. Comparisons between the skill levels of the model forecasts and forecasts of persisted sea surface temperature anomalies during January–May show that the model starts to outscore persistence at a lead time of only 3 months. Useful skill is indicated for the persistence forecasts only for the July–October period, while poor model skill is evident during the last third of the year. The good performance of the model for the later part of the boreal winter and spring is due to the strong association between the leading EOF of the sea surface temperatures of the Indian Ocean and ENSO (Cadet 1985).

Strongest skill in forecasts of equatorial Indian Ocean sea surface temperatures is achieved for April (Fig. 5). For forecasts of April sea surface temperatures, skill remains more or less constant over lead times of almost 1 yr (Fig. 6), as is the case for the equatorial Pacific. The high skill found for the equatorial Indo-Pacific regions is reflected in the model's ability to forecast most of the strong events during the 18-yr retroactive period with high accuracy, albeit with decreasing sea surface temperature anomaly amplitude with increasing lead time. Because the leading EOF mode of the predictor set is associated with ENSO, the quasistationarity in April skill (produced by the CCA model) with increasing lead time is probably the same as for the equatorial Pacific Ocean: part of the Indo-Pacific ENSO signal

usually persists into April and can be forecast successfully during the developing and mature phases of the ENSO cycle.

Generally poor forecast skill is found for predictions of boreal autumn equatorial Indian Ocean sea surface temperatures (Fig. 5). Although the model was successful in predicting the anomalously warm conditions of the most recent decades, specific warm and cold events during autumn were forecast poorly. Forecast skill is poor during these boreal autumn months when the so-called Indian Ocean dipole mode is active (Saji et al. 1999; Webster et al. 1999). This dipole mode involves a pattern of variability with anomalously low sea surface temperatures off Sumatra and anomalously high sea surface temperatures in the western Indian Ocean. Such an event occurred during the development stages of the strong 1997/98 El Niño event. The inability to forecast the dipole variability accurately is of concern because it is thought to have an important influence on rainfall variability in some parts of Africa, for example (Bazira and Ogallo 1999).

### c. Equatorial Atlantic Ocean

Retroactive forecast values for the equatorial Atlantic Ocean index are shown in Fig. 7. The temporal correlations between the observed and predicted indices over the  $18 \times 12$  months are 0.40, 0.36, 0.21, and 0.16 for



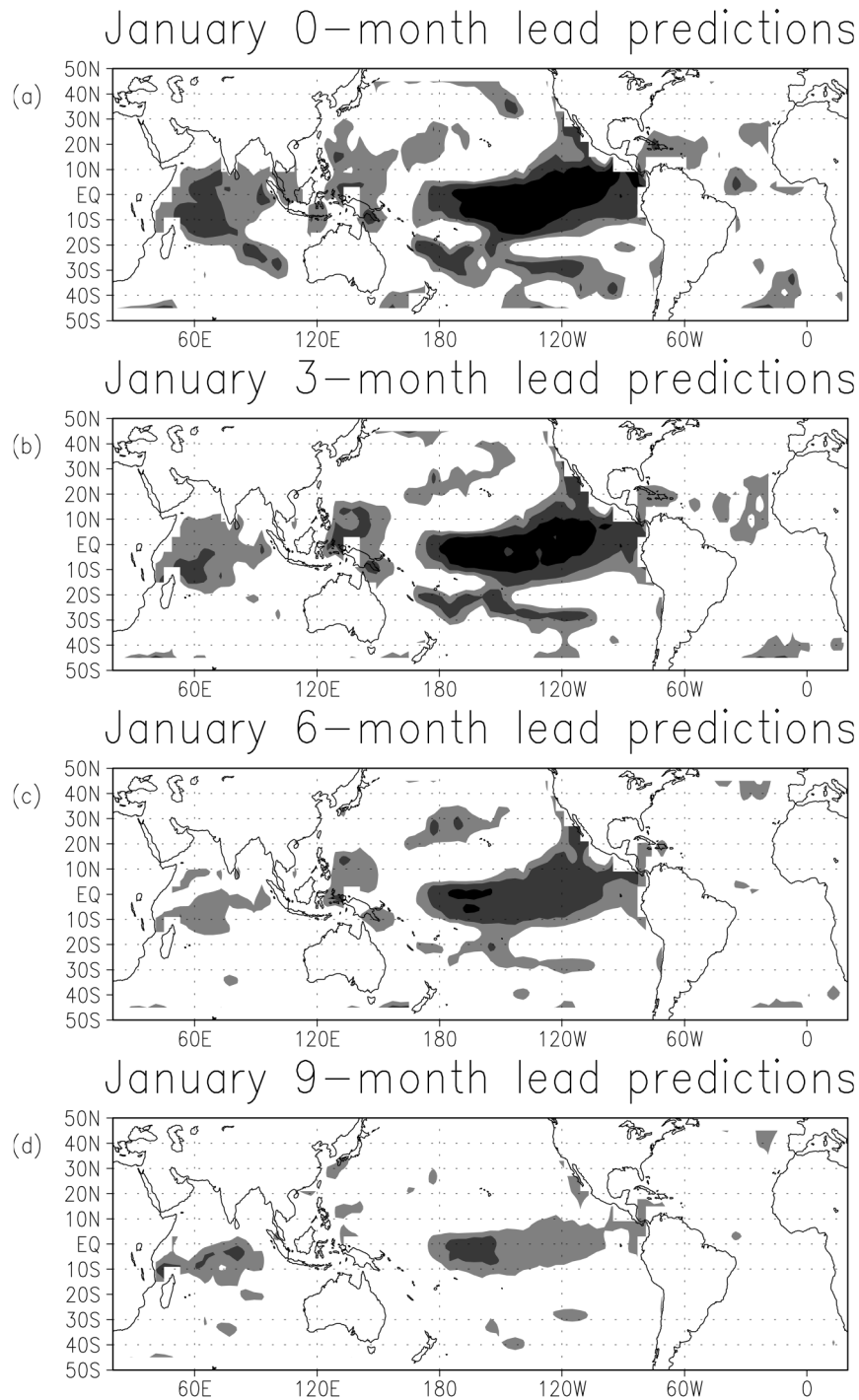
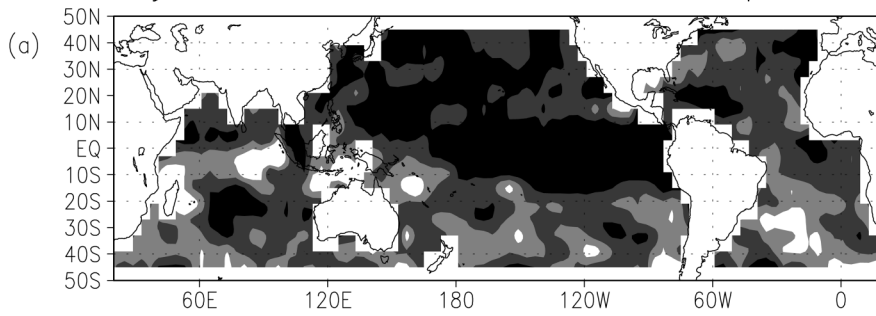
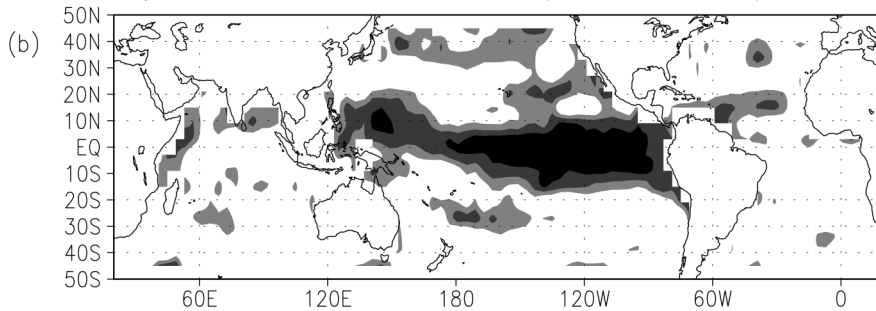


FIG. 9. Temporal correlations between observed and predicted Jan sea surface temperature anomalies at (a) 0-month, (b) 3-month, (c) 6-month, and (d) 9-month lead times over the 18-yr retroactive forecast period 1983–2000. Correlations larger than 0.4 are shaded light gray, larger than 0.6 dark gray, and larger than 0.8 black.

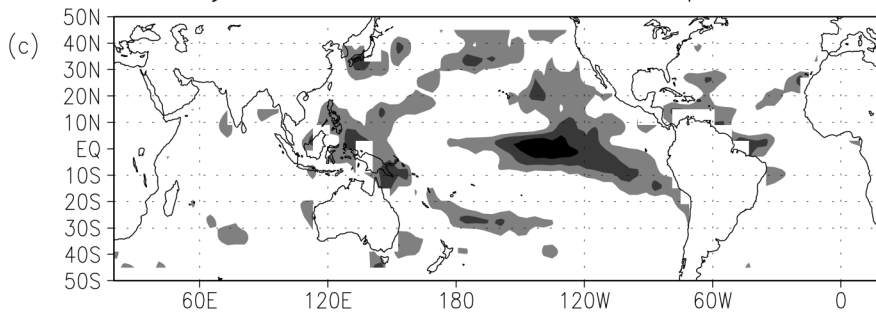
## January observed vs December persistence



## January observed vs September persistence



## January observed vs June persistence



## January observed vs March persistence

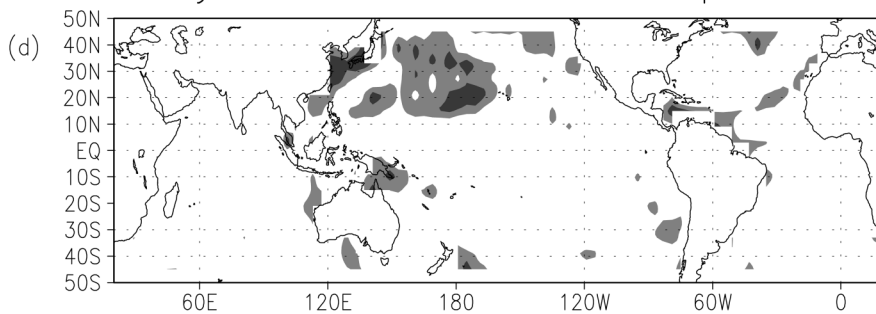


FIG. 10. Temporal correlations between observed Jan sea surface temperature anomalies and anomalies persisted from (a) Dec, (b) Sep, (c) Jun, and (d) Mar. Correlations are calculated over the 18-yr period 1983–2000. Correlations larger than 0.4 are shaded light gray, larger than 0.6 dark gray, and larger than 0.8 black.

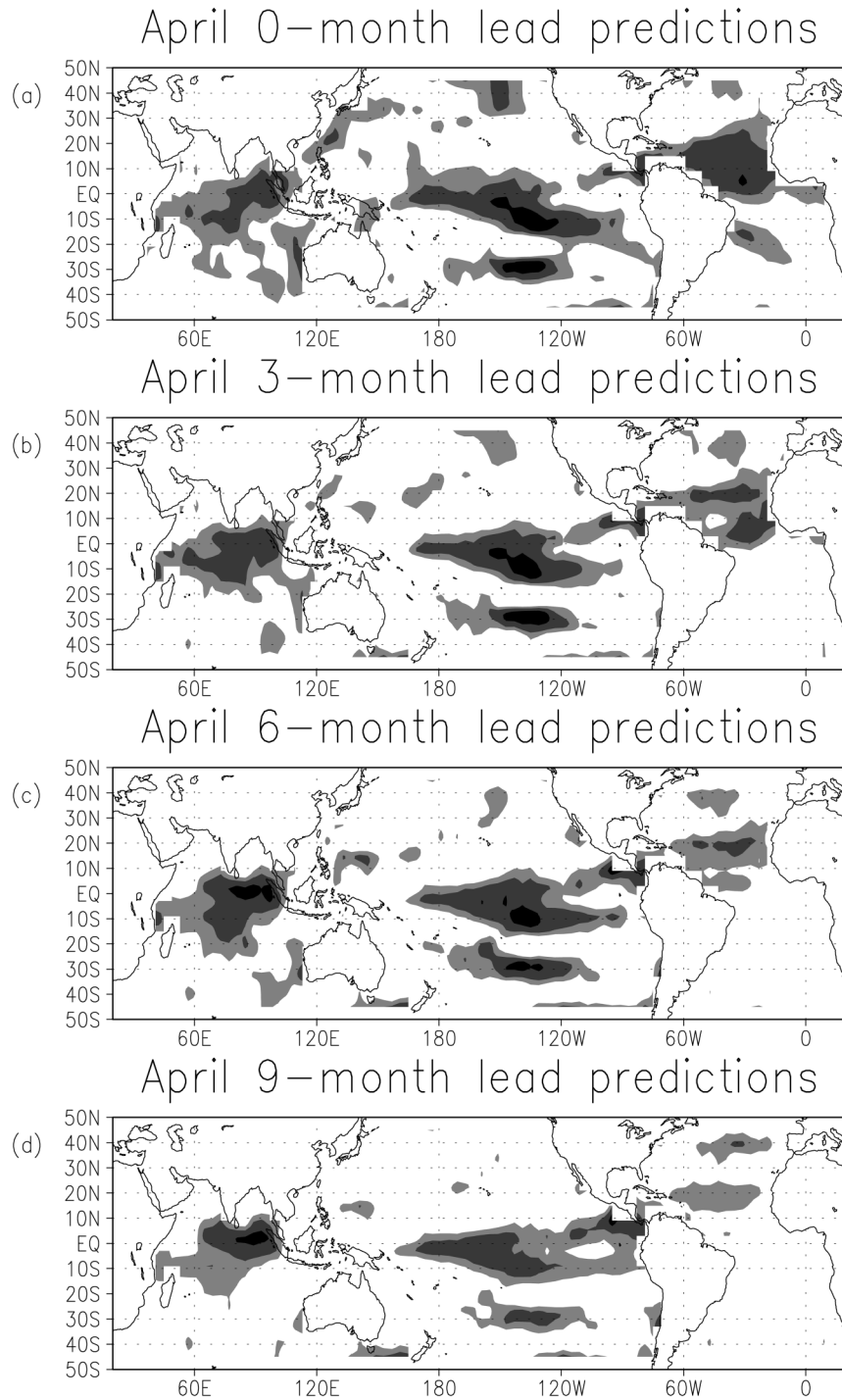


FIG. 11. Temporal correlations between observed and predicted Apr sea surface temperature anomalies at (a) 0-month, (b) 3-month, (c) 6-month, and (d) 9-month lead times over the 18-yr retroactive forecast period 1983–2000. Correlations larger than 0.4 are shaded light gray, larger than 0.6 dark gray, and larger than 0.8 black.

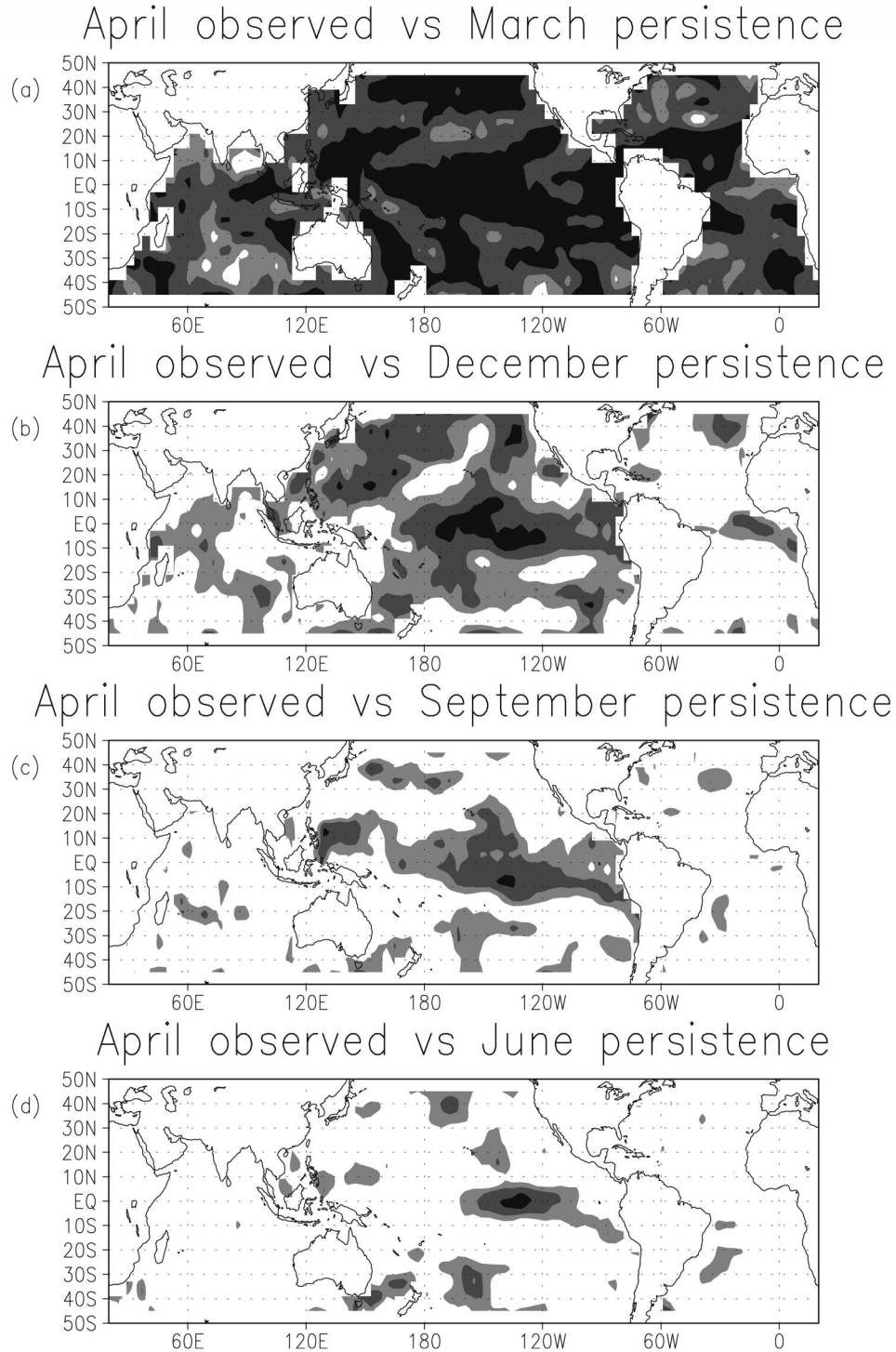


FIG. 12. Temporal correlations between observed Apr sea surface temperature anomalies and anomalies persisted from (a) Mar, (b) Dec, (c) Sep, and (d) Jun. Correlations are calculated over the 18-yr period 1983–2000. Correlations larger than 0.4 are shaded light gray, larger than 0.6 dark gray, and larger than 0.8 black.

the 0-, 3-, 6-, and 9-month lead times, respectively. These retroactive correlations are poor and considerably lower than those for the eastern equatorial Pacific Ocean and the equatorial Indian Ocean. However, the model did successfully anticipate the warmer than average period of the equatorial Atlantic Ocean that has occurred since the late 1970s and, which is not reflected in the correlations. As for the Indian Ocean, the variance of the observed sea surface temperatures is low.

Figure 8 shows the annual cycle of correlations between the observed and predicted, and the observed and persisted sea surface temperature anomalies at 0-, 3-, 6-, and 9-month lead times as obtained over the retroactive period of 18 yr. For the 0- and 3-month lead times, the forecasts for January–March indicate reasonable skill. The skill for these months may be related to the way the ENSO signal is transferred to the Atlantic Ocean, particularly just to the northern side of the equator, a few months after the mature event in the Pacific Ocean (Barnston 1994). Of the three equatorial basins considered, the predictive skill for the equatorial Atlantic Ocean temperatures is the lowest, and forecast of persisted anomalies are better than the model forecasts in most instances. Since equatorial Atlantic sea surface temperatures do have an important influence on climate variability in some regions (Ward and Folland 1991; Lamb and Pepler 1992; Mason and Jury 1997), it would be useful to be able to predict sea surface temperatures of the Atlantic Ocean skillfully.

#### 4. Forecasts of global sea surface temperatures

It has been shown above that the statistical model described in this paper has the potential to provide useful predictions of equatorial Pacific and Indian Ocean sea surface temperatures. The forecast skill presented here for the equatorial Pacific sea surface temperature compares well with skill levels of other models for predicting equatorial Pacific Ocean variability. For the equatorial Indian Ocean, forecasts of persisted anomalies have been outscored for most of the boreal winter and spring seasons. Forecast skill for the Atlantic Ocean basin is relatively poor, but is mainly positive. In this section the predictability of the oceans outside the Tropics is investigated.

Maps of the retroactive temporal correlations between the predicted and observed, and persistence and observed January and April sea surface temperature anomalies are shown in Figs. 9–12 for all  $6^\circ \times 4^\circ$  grid boxes. January and April are discussed in detail here because of the relatively high forecast skill for these months. The shaded areas of useful model skill (Figs. 9 and 11) can be compared with forecasts using persisted sea surface temperature anomalies (Figs. 10 and 12). For predicting January sea surface temperature anomalies, December, September, June, and March anomalies are persisted, which correspond with 0-, 3-, 6-, and 9-month lead times, respectively. For April anomalies, March, December, September, and June anomalies are persisted.

Areas with highly skillful forecasts decrease with increasing lead times, but the reduction is much faster for the forecasts of persisted anomalies. For both forecast methods, skill is greatest over the equatorial Pacific Ocean basin and areas over the tropical Indian and Atlantic Oceans. In general, forecasts of sea surface temperatures outside the Tropics have not been skillful. However, although forecasts of persisted anomalies indicate skill over larger areas than the model predictions at a 0-month lead time, the model is clearly superior at the longest lead times.

#### 5. Summary and discussion

Useful skill in predicting sea surface temperatures has been demonstrated in the past by using a wide range of statistically and dynamically based forecast models. Global interest has focused on the predictability of the equatorial Pacific sea surface temperature because of its impact on worldwide climate variability. However, the climate in many parts of the world is affected by the variability of ocean temperatures in areas beyond the equatorial Pacific. In addition, global sea surface temperature anomaly forecasts are required by general circulation models used in a two-tiered forecasting procedure when predicting rainfall and surface temperatures.

The forecast model described in this paper uses evolutionary features of the global oceans as predictors of sea surface temperatures for individual months. Forecasts of consecutive monthly temperatures were obtained for an independent 18-yr retroactive period. The forecasts of eastern equatorial Pacific Ocean sea surface temperatures showed high skill for lead times up to several seasons, and a high degree of accuracy in predicting the amplitudes of many of the strongest ENSO events. However, model skill only outscored skill levels obtained from persistence of sea surface temperature anomalies as a forecast beyond two seasons. Similarly, significant skill levels have been found for the equatorial Indian Ocean. Although the skill levels for this ocean have been lower than those of the equatorial Pacific Ocean, the model forecast skill for the equatorial Indian Ocean outscored persistence only after about 3 months. The skill is limited to the boreal spring months with a maximum skill level obtained during April, and does not produce a recovery in forecast skill toward the autumn months, as is the case of the equatorial Pacific Ocean. The predictability of the tropical Atlantic Ocean and of sea surface temperatures outside the Tropics is considerably less than that of the other two tropical oceans.

The predictability of the tropical Pacific and Indian Ocean sea surface temperatures seems to have weakened during the early and mid-1990s. After accurate predictions of the 1988/89 La Niña event, the model underestimated the strength of the subsequent ENSO events during the first half of the 1990s. The poor predictability



of the tropical Pacific sea surface temperatures during this period has also been found with other prediction models, both statistical and dynamical. For the tropical Indian Ocean, a loss of predictability seems to have occurred after 1989 (Fig. 4). Forecasts for both these ocean basins improved again toward the end of the 1990s, as reflected in the successful forecasts of the sea surface temperature anomalies during the strong 1997/98 El Niño and subsequent La Niña events of 1998/99 and 1999/2000.

The model presented in this paper does show some useful skill in predicting tropical sea surface temperatures. It has been tested vigorously in retroactive mode over an 18-yr period, which includes the first half of the 1990s, a period that generally is considered to be one of poor predictability. The retroactive testing provides a true indication of operational forecast skill. Persistence was shown to be producing skill levels similar to what was found using the model forecasts over the equatorial Pacific Ocean over lead times up to two seasons, and was found to be of significant importance during the boreal summer over the Indian Ocean and during late spring and early summer over the equatorial Atlantic Ocean. The model outperformed forecasts of persisted anomalies of the equatorial Indian Ocean after a couple of months, but significant model skill is restricted to the boreal spring. For the Atlantic Ocean, the model only outscores persistence on rare occasions. Persistence remained the best strategy at short lead times (1 or 2 months) for any part of the global oceans considered. Consequently, for short lead times and in the extratropics, until such time that predicted sea surface temperature fields can be improved significantly, possibly with the use of subsurface and other data (Johnson et al. 2000; Xue et al. 2000), persistence will remain a strong competitor.

*Acknowledgements.* This research was supported in part by the Postdoctoral Program at the International Research Institute for Climate Prediction, administered by the University Corporation for Atmospheric Research, and by a grant/cooperative agreement from the National Oceanic and Atmospheric Administration (NOAA) (NAO7GP0213). The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA or any of its subagencies. Comments and suggestions by Tony Barnston and anonymous referees are gratefully acknowledged.

#### REFERENCES

- Anderson, D. L. T., and M. K. Davey, 1998: Predicting the El Niño of 1997/98. *Weather*, **53**, 303–310.
- Barnett, T. P., 1984: Prediction of the El Niño of 1982–83. *Mon. Wea. Rev.*, **112**, 1403–1407.
- Barnston, A. G., 1994: Linear statistical short-term climate predictive skill in the Northern Hemisphere. *J. Climate*, **7**, 1513–1564.
- , and C. F. Ropelewski, 1992: Prediction of ENSO using canonical correlation analysis. *J. Climate*, **5**, 1316–1345.
- , and Coauthors, 1994: Long-lead seasonal forecasts—Where do we stand? *Bull. Amer. Meteor. Soc.*, **75**, 2097–2114.
- , M. H. Glantz, and Y. He, 1999: Predictive skill of statistical and dynamical climate models in SST forecasts during the 1997–98 El Niño episode and the 1998 La Niña onset. *Bull. Amer. Meteor. Soc.*, **80**, 217–244.
- Bazira, E., and L. A. Ogallo, 1999: Potential of seasonal rainfall prediction over East Africa as derived from sea-surface temperature (SST) modes of neighbouring oceans. *J. Afr. Meteor. Soc.*, **4**, 63–80.
- Burgers, G., 1999: The El Niño stochastic oscillator. *Climate Dyn.*, **15**, 521–531.
- Cadet, D. L., 1985: The Southern Oscillation over the Indian Ocean. *J. Climatol.*, **5**, 189–212.
- Chen, D., S. E. Zebiak, A. J. Busalacchi, and M. A. Cane, 1995: An improved procedure for El Niño forecasting: Implications for predictability. *Science*, **269**, 1699–1702.
- Clarke, A. J., and B. Li, 1995: On the timing of warm and cold El Niño–Southern Oscillation events. *J. Climate*, **8**, 2571–2574.
- Enfield, D. B., 1996: Relationships of inter-American rainfall to tropical Atlantic and Pacific SST variability. *Geophys. Res. Lett.*, **23**, 3305–3308.
- Fontaine, B., S. Janicot, and P. Roucou, 1999: Ocean ocean–atmosphere surface variability and its climate impacts in the tropical Atlantic region. *Climate Dyn.*, **15**, 451–473.
- Glantz, M. H., 1994: *Drought Follows the Plow*. Cambridge University Press, 197 pp.
- Goddard, L., and N. E. Graham, 1997: El Niño in the 1990s. *J. Geophys. Res.*, **102**, 10 423–10 436.
- , and —, 1999: The importance of the Indian Ocean for simulating rainfall anomalies over eastern and southern Africa. *J. Geophys. Res.*, **104**, 10 423–10 436.
- , S. J. Mason, S. E. Zebiak, C. F. Ropelewski, R. Basher, and M. A. Cane, 2001: Current approaches to seasonal to interannual climate predictions. *Int. J. Climatol.*, in press.
- Hunt, B. G., S. E. Zebiak, and M. A. Cane, 1994: Experimental predictions of climate variability for lead times of twelve months. *Int. J. Climatol.*, **14**, 507–526.
- Jackson, J. E., 1991: *A Users' Guide to Principal Components*. Wiley, 569 pp.
- Janicot, S., A. Harzallah, B. Fontaine, and V. Moron, 1998: West African monsoon dynamics and eastern equatorial Atlantic and Pacific SST anomalies (1970–83). *J. Climate*, **11**, 412–430.
- Ji, M., A. Leetmaa, and V. E. Kousky, 1996: Coupled model prediction of ENSO during the 1980s and the 1990s at the National Centers for Environmental Prediction. *J. Climate*, **9**, 3105–3120.
- Johnson, S. D., D. S. Battisti, and E. S. Sarachik, 2000: Empirically derived Markov models and prediction of tropical Pacific sea surface temperature anomalies. *J. Climate*, **13**, 3–17.
- Jolliffe, I. T., 1972: Discarding variables in principal component analysis. I: Artificial data. *Appl. Stat.*, **21**, 160–173.
- Kane, R. P., 1997: Prediction of droughts in north-east Brazil: Role of ENSO and use of periodicities. *Int. J. Climatol.*, **17**, 655–665.
- , 1999: Rainfall extremes in some selected parts of Central and South America: ENSO and other relationships reexamined. *Int. J. Climatol.*, **19**, 423–455.
- Kawamura, R., 1994: A rotated EOF analysis of global sea surface temperature variability with interannual and interdecadal scales. *J. Phys. Oceanogr.*, **24**, 707–715.
- Kirtman, B. P., and P. S. Schopf, 1998: Decadal variability in ENSO predictability and prediction. *J. Climate*, **11**, 2804–2822.
- Lamb, P. J., and R. A. Pepler, 1992: Further case studies of tropical Atlantic surface atmospheric and oceanic patterns associated with sub-Saharan drought. *J. Climate*, **5**, 476–488.
- Landman, W. A., 1997: A study of the predictability of the equatorial Indian Ocean sea-surface temperatures. Preprints, *Fifth Int. Conf. on Southern Hemisphere Meteorology and Oceanography*, Pretoria, South Africa, Amer. Meteor. Soc., 140–141.
- , and S. J. Mason, 1999: Change in the association between



- Indian Ocean sea surface temperatures and summer rainfall over South Africa and Namibia. *Int. J. Climatol.*, **19**, 1477–1492.
- , —, P. D. Tyson, and W. J. Tennant, 2001: Retro-active skill of multi-tiered forecasts of summer rainfall over southern Africa. *Int. J. Climatol.*, **21**, 1–19.
- Landsea, C. W., and J. A. Knaff, 2000: How much “skill” was there in forecasting the Great 1997–98 El Niño? *Bull. Amer. Meteor. Soc.*, **81**, 2107–2120.
- Mantua, N. J., and D. S. Battisti, 1994: Evidence for the delayed-oscillator mechanism for ENSO: The “observed” Kelvin model in the far western Pacific. *J. Phys. Oceanogr.*, **24**, 691–699.
- Mason, S. J., 1995: Sea-surface temperature–South African rainfall associations, 1910–1989. *Int. J. Climatol.*, **15**, 119–135.
- , 1997: Recent changes in El Niño–Southern Oscillation events and their implications for southern African climate. *Trans. Roy. Soc. South Afr.*, **52**, 377–403.
- , and M. R. Jury, 1997: Climate variability and change over southern Africa: A reflection on underlying processes. *Prog. Phys. Geogr.*, **21**, 23–50.
- , and P. D. Tyson, 2000: The occurrence and predictability of droughts over southern Africa. *A Global Assessment*, D. A. Wilhite, Ed., Vol. 1, *Drought*, Routledge, 113–134.
- , L. Goddard, N. E. Graham, E. Yulaeva, L. Sun, and P. A. Arkin, 1999: The IRI seasonal climate prediction system and the 1997/98 El Niño event. *Bull. Amer. Meteor. Soc.*, **80**, 1853–1873.
- Ming, J., A. Leetmaa, and V. E. Kousky, 1996: Coupled model predictions of ENSO during the 1980s and 1990s at the National Centers for Environmental Prediction. *J. Climate*, **9**, 3105–3120.
- Moore, A. M., and R. Kleeman, 1998: Skill assessment for ENSO using ensemble prediction. *Quart. J. Roy. Meteor. Soc.*, **124**, 557–584.
- Moron, V., S. Bigot, and P. Roucou, 1995: Rainfall variability in subequatorial America and Africa and relationships with the main sea-surface temperature modes (1951–1990). *Int. J. Climatol.*, **15**, 1297–1322.
- Moura, A. D., 1994: Prospects for seasonal-to-interannual climate prediction and applications for sustainable development. *WMO Bull.*, **43**, 207–215.
- , and E. S. Sarachik, 1997: Seasonal-to-interannual climate prediction and applications: New institutions, new possibilities. *WMO Bull.*, **46**, 342–347.
- , and Coauthors, 1992: *International Research Institute for Climate Prediction: A Proposal*. NOAA Office of Global Programs, 51 pp.
- National Research Council, 1996: *Learning to Predict Climate Variations Associated with El Niño and the Southern Oscillation. Accomplishments and Legacies of the TOGA Program*. National Academy Press, 171 pp.
- Navarra, A., M. N. Ward, and N. A. Rayner, 1998: A stochastic model of SST for climate simulation experiments. *Climate Dyn.*, **14**, 473–487.
- Nobre, P., and I. F. A. Cavalcanti, 1999: The prediction of drought in the Brazilian Nordeste: Progress and prospects for the future. *A Global Assessment*, D. A. Wilhite, Ed., Vol. 1, *Drought*, Routledge, 68–82.
- Penland, C., and P. D. Sardeshmukh, 1995: The optimal growth of tropical sea surface temperature anomalies. *J. Climate*, **8**, 1999–2024.
- , and L. Matrosova, 1998: Prediction of tropical Atlantic sea surface temperatures using linear inverse modeling. *J. Climate*, **11**, 483–496.
- Pezzi, L. P., C. R. Repelli, P. Nobre, I. F. A. Cavalcanti, and G. Sampaio, 1998: Forecasts of tropical Atlantic SST using a statistical ocean model at CPTEC/INPE—Brazil. *Exp. Long-Lead Forecast Bull.*, **7**, 28–31.
- Philander, S. G., 1998: Learning from El Niño. *Weather*, **53**, 270–274.
- Reynolds, R. W., and T. M. Smith, 1994: Improved global sea surface temperature analyses using optimum interpolation. *J. Climate*, **7**, 929–948.
- Rocha, A., and I. Simmonds, 1997: Interannual variability of southeastern African summer rainfall. Part I: Relationships with air–sea interaction processes. *Int. J. Climatol.*, **17**, 235–266.
- Saji, N. H., B. N. Goswami, P. N. Vinayachandran, and T. Yamagata, 1999: A dipole mode in the tropical Indian Ocean. *Nature*, **401**, 360–363.
- Semazzi, F. H. M., V. Mehta, and Y. C. Sud, 1988: An investigation of the relationship between sub-Saharan rainfall and global sea-surface temperatures. *Atmos.–Ocean*, **26**, 118–138.
- Smith, T. M., R. W. Reynolds, R. E. Livezey, and D. C. Stokes, 1996: Reconstruction of historical sea surface temperatures using empirical orthogonal functions. *J. Climate*, **9**, 1403–1420.
- Stockdale, T. N., D. L. T. Anderson, J. O. S. Alves, and M. A. Balmaseda, 1998: Global seasonal rainfall forecasts using a coupled ocean–atmosphere model. *Nature*, **392**, 370–373.
- Suarez, M. J., and P. S. Schopf, 1988: A delayed action oscillator for ENSO. *J. Atmos. Sci.*, **45**, 3283–3287.
- Tangang, F. T., B. Tang, A. H. Monahan, and W. W. Hsieh, 1998: Forecasting ENSO events: A neural network–extended EOF approach. *J. Climate*, **11**, 29–41.
- Tennant, W. J., 1996: Influence of Indian Ocean sea-surface temperature anomalies on the general circulation of southern Africa. *South Afr. J. Sci.*, **92**, 289–295.
- Trenberth, K. E., and J. W. Hurrell, 1994: Decadal atmosphere–ocean variations in the Pacific. *Climate Dyn.*, **9**, 303–319.
- Ward, M. N., 1998: Diagnosis and short-lead time prediction of summer rainfall in tropical North Africa at interannual and multi-decadal timescales. *J. Climate*, **11**, 3167–3191.
- , and C. K. Folland, 1991: Prediction of seasonal rainfall in the north Nordeste of Brazil using eigenvectors of sea-surface temperature. *Int. J. Climatol.*, **11**, 711–743.
- Webster, P. J., A. M. Moore, J. P. Loschnigg, and R. R. Leben, 1999: Coupled ocean–atmosphere dynamics in the Indian Ocean during 1997–98. *Nature*, **401**, 356–360.
- Xue, Y., M. A. Cane, S. E. Zebiak, and M. B. Blumenthal, 1994: On the prediction of ENSO: A study with a low-order Markov model. *Tellus*, **46A**, 512–528.
- , A. Leetmaa, and M. Ji, 2000: ENSO prediction with Markov models: The impact of sea level. *J. Climate*, **13**, 849–871.
- Zebiak, S. E., 1993: Air–sea interaction in the equatorial Atlantic region. *J. Climate*, **6**, 1567–1586.
- , and M. A. Cane, 1987: A model El Niño–Southern Oscillation. *Mon. Wea. Rev.*, **115**, 2262–2278.