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A review of the predictability and prediction of ENSO

M. Latif,[1] D. Anderson,[2] T. Barnett,[3] M. Cane,[4] R. Kleeman,[5] A. Leetmaa,[6]
J. O'Brien,[7] A. Rosati,[8] and E. Schneider[9]

Abstract. A hierarchy of El Niño–Southern Oscillation (ENSO) prediction schemes has been developed during the Tropical Ocean–Global Atmosphere (TOGA) program which includes statistical schemes and physical models. The statistical models are, in general, based on linear statistical techniques and can be classified into models which use atmospheric (sea level pressure or surface wind) or oceanic (sea surface temperature or a measure of upper ocean heat content) quantities or a combination of oceanic and atmospheric quantities as predictors. The physical models consist of coupled ocean-atmosphere models of varying degrees of complexity, ranging from simplified coupled models of the "shallow water" type to coupled general circulation models. All models, statistical and physical, perform considerably better than the persistence forecast in predicting typical indices of ENSO on lead times of 6 to 12 months. The TOGA program can be regarded as a success from this perspective. However, despite the demonstrated predictability, little is known about ENSO predictability limits and the predictability of phenomena outside the tropical Pacific. Furthermore, the predictability of anomalous features known to be associated with ENSO (e.g., Indian monsoon and Sahel rainfall, southern African drought, and off-equatorial sea surface temperature) needs to be addressed in more detail. As well, the relative importance of different physical mechanisms (in the ocean or atmosphere) has yet to be established. A seasonal dependence in predictability is seen in many models, but the processes responsible for it are not fully understood, and its meaning is still a matter of scientific discussion. Likewise, a marked decadal variation in skill is observed, and the reasons for this are still under investigation. Finally, the different prediction models yield similar skills, although they are initialized quite differently. The reasons for these differences are also unclear.

1. Introduction

The El Niño–Southern Oscillation (ENSO) phenomenon is the strongest climate variation on the short-range climatic timescale ranging from a few months to several years. ENSO is characterised by an irregular interannual oscillation of tropical Pacific sea surface temperatures (SSTs). The warm phase of ENSO is often referred to as "El Niño," while the cold phase is often referred to as "La Niña" or "El Viejo." Although ENSO originates in the tropical Pacific, it affects not only regional but also global climate [e.g., *Ropelewski and Halpert*, 1989; *Glantz et al.*, 1991]. ENSO-related climate anomalies are described in many papers, and the reader is referred to the review papers by *Wallace et al.* [this issue, and references therein] and *Trenberth et al.* [this issue, and references therein] to obtain more details.

The warm ENSO extremes, for instance, are connected with anomalous dry conditions over Southeast Asia and northeast Australia and anomalous wet conditions over some parts of South America (e.g., Peru and Chile). Significant ENSO-related climate anomalies are also reported over the United States [*Horel and Wallace*, 1981] and even over Europe [*Fraedrich*, 1994]. However, ENSO affects not only regional and global climate but also the ecosystems in and around the tropical Pacific and the economies of several countries. The successful prediction of ENSO is therefore not only of scientific but also of practical interest.

One of the main goals of the international Tropical Ocean–Global Atmosphere (TOGA) program was the development of ENSO forecast models, and this goal was achieved, as witnessed by the variety of ENSO prediction models that were applied successfully to predict the low-frequency changes of typical ENSO indices. The intention behind this paper is to describe the development and performance of the forecast models and to assess critically the level of understanding concerning ENSO predictability. Results from the different forecast models were not available in a common format, and we would like to point out that this review paper is not meant to be an intercomparison paper. Many problems were not fully addressed during the TOGA program, and those need to be considered in more detail in the near future in order to obtain a more complete understanding of ENSO predictability. There

[1]Max-Planck-Institut für Meteorologie, Hamburg, Germany.
[2]Department of Atmospheric Physics, Clarendon Laboratory, Oxford, England, United Kingdom.
[3]Climate Research Division, Scripps Institution of Oceanography, La Jolla, California.
[4]Lamont-Doherty Earth Observatory, Columbia University, Palisades, New York.
[5]Bureau of Meteorology Research Centre, Melbourne, Victoria, Australia.
[6]Coupled Model Project, National Meteorological Center, Camp Springs, Maryland.
[7]Center for Ocean-Atmosphere Prediction Studies, Florida State University, Tallahassee.
[8]Geophysical Fluid Dynamics Laboratory, NOAA, Princeton University, Princeton, New Jersey.
[9]Center for Ocean-Land-Atmosphere Studies, Calverton, Maryland.

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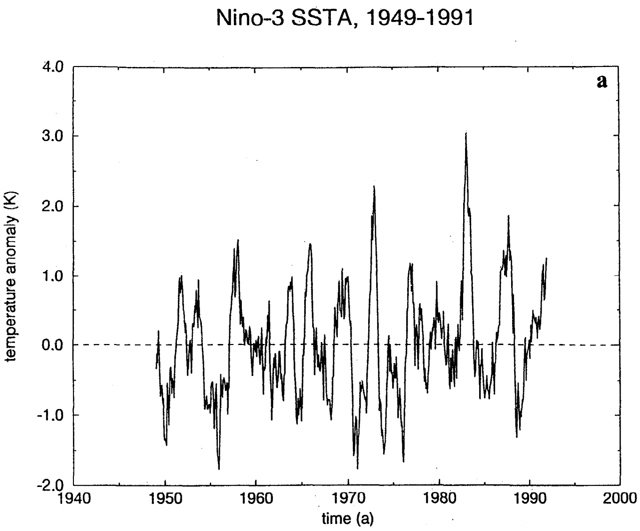

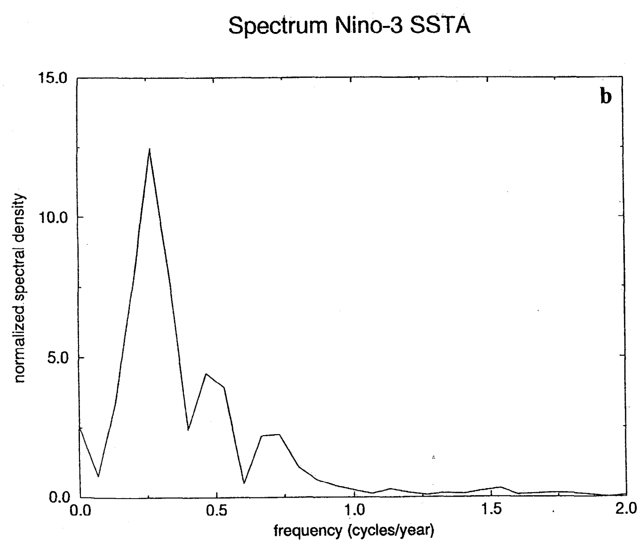

Figure 1. (a) Time series of eastern equatorial sea surface temperature (SST) anomalies (degrees Celsius) averaged over the Niño 3 region for the period 1949–1991, as derived from the Global Ice Sea Surface Temperature (GISST) data set. (b) Fourier spectrum of the Niño 3 time series. A Bartlett procedure with a window length of 180 months was chosen yielding 4 degrees of freedom. From *Latif et al.* [1996].

is, for instance, no commonly accepted skill measure that would describe a forecast model's ability to predict ENSO. It is also not clear what the most adequate observational network is for providing the initial conditions from which to make the most accurate forecasts. Furthermore, there is no consensus about a standard set of predictands to be used. These are only three important questions that have yet to be addressed by the community to obtain a more complete understanding of ENSO. Such issues will be dealt with within the Global Ocean-Atmosphere-Land System (GOALS) component of the international Climate Variability and Predictability (CLIVAR) program. Other reviews on ENSO forecasting can be found in works by *Barnett et al.* [1988], *Latif et al.* [1994], and *Barnston et al.* [1994]. Not all the papers addressing the issue of ENSO prediction and predictability can be described here. A rather complete reference list, which was compiled by E. Sarachik during the U.S. TOGA Program on Prediction (TPOP), is available at the following internet address: http://www.atmos.washington.edu/tpop/pop.htm. We discuss in this paper only a subset of the existing prediction models. We believe that these models were most influential in stimulating further research. This is, however, a subjective choice and might not reflect the views of other groups.

Short-range climate forecasting has a long history: *Walker* [1923, 1924], the discoverer of the Southern Oscillation, studied global pressure variations in order to predict anomalies in the Indian monsoon rainfall. Although Walker failed in predicting the strength of the Indian monsoon, his work turned out to be very influential. Many years later, *Bjerknes* [1969] linked the Southern Oscillation to the tropical Pacific sea surface temperature, and he introduced the concept of unstable air-sea interactions and postulated the existence of a climate cycle which is inherently predictable.

Statistical methods were applied to the problem of short-range climate forecasting in the late 1970s and early 1980s [*Barnett and Hasselmann*, 1979; *Hasselmann and Barnett*, 1981], and these early studies showed clearly that ENSO is predictable a few seasons ahead. *Inoue and O'Brien* [1984] were the first to apply a physical ocean model to ENSO forecasting and attained some skill in predicting the onset of major ENSO extremes at lead times of a few months. *Cane et al.* [1986] in their pioneering work were the first to apply successfully a simplified but fully physical coupled ocean-atmosphere model [*Zebiak and Cane*, 1987] to ENSO forecasts. This work was followed by many more prediction and predictability studies, using a coupled ocean-atmosphere general circulation model (CGCM) to perform ensemble predictions of ENSO [e.g., *Latif et al.*, 1993b]. These early studies, however, made no use of oceanic data to initialize ENSO forecasts. Two groups then developed integrated data assimilation/coupled general circulation model forecasting systems [*Ji et al.*, 1994a; *Rosati et al.*, 1995]. About a dozen forecasting models are now applied routinely, including statistical and physical models, and the forecast results are published in the U.S. National Oceanic and Atmospheric Administration (NOAA) Forecast Bulletin.

The paper is organized as follows. We describe in section 2 the scientific basis for ENSO prediction. Section 3 deals with the performance of the statistical forecast models, and section 4 deals with that of the coupled ocean-atmosphere models. In section 5 we describe the "two-tiered approach," while some skill sensitivities are discussed in section 6. Section 7 deals with the other two tropical oceans. The paper concludes with a discussion in section 8.

2. Scientific Basis for ENSO Prediction

A principal characteristic of the ENSO phenomenon is its quasiperiodicity. This can be inferred, for instance, from the spectra of typical ENSO indices, such as the Niño 3 index (Figure 1a), which is an area average of eastern equatorial Pacific SST anomalies over the region 5°N–5°S and 150°–90°W and a good proxy for the state of the tropical ocean-atmosphere system. The corresponding spectrum of the Niño 3 time series (Figure 1b) exhibits enhanced variability levels at interannual timescales, with the dominant peak centered at a period of about 4 years and a secondary peak at a quasi-biennial timescale, features that are well established in the literature [e.g., *Rasmusson and Carpenter*, 1982]. It is the existence of these peaks which suggests that ENSO may be predictable with a lead time of more than a year.

Different competing hypotheses were offered to explain the cyclic nature of ENSO. However, it is now commonly believed that ENSO is a fundamental oscillatory mode of the coupled ocean-atmosphere system and that the memory of the coupled system resides in the ocean thermocline state [see *Neelin et al.*, this issue]. An alternative hypothesis that assigns extratropical processes an active role will be described below when we discuss the statistical prediction models. The importance of the subsurface memory, as expressed by slow variations in the equatorial Pacific upper ocean heat content, for the ENSO phenomenon has been shown in many observational and modeling studies [e.g., *Wyrtki*, 1975, 1985; *Cane and Sarachik*, 1981; *Busalacchi et al.*, 1983; *McCreary*, 1983; *White et al.*, 1987; *Zebiak and Cane*, 1987; *Schopf and Suarez*, 1988; *Graham and White*, 1988; *Kessler*, 1990, 1991; *Philander et al.*, 1992; *Chao and Philander*, 1993; *Latif and Graham*, 1992; *Latif et al.*, 1993a, b; *McPhaden et al.*, this issue]. A conceptual model, the "delayed action oscillator" was proposed independently by *Suarez and Schopf* [1988] and *Battisti and Hirst* [1989] [see also *Battisti*, 1988; *Cane et al.*, 1990; *Chao and Philander*, 1993; *Schneider et al.*, 1995], which summarizes the fundamental zeroth-order physics involved in ENSO and explains its cyclic nature. References and a summary of the observational evidence that supports the delayed oscillator physics for ENSO can be found in the recent review paper by *Battisti and Sarachik* [1995].

According to the delayed action oscillator scenario the easterly wind anomalies over the western Pacific prevailing during the cold phase of the ENSO cycle force an upwelling Kelvin wave packet, which propagates eastward along the equator and causes cooling at the sea surface in the eastern Pacific, where the thermocline is shallow. The ocean response to the easterly winds in the west, however, consists also of a downwelling Rossby wave packet, which propagates westward. This Rossby wave response has its strongest signals off the equator. It does not influence the SST in these regions because the thermocline is deep in the western Pacific. The Rossby waves then reflect at the western boundary into a packet of downwelling Kelvin waves, which have maximum amplitudes at the equator and propagate eastward. Once it has propagated far enough into the eastern Pacific, it is able to affect the SST, and a positive SST anomaly develops, which can grow by unstable air-sea interactions into the warm phase of ENSO. Thereafter the sequence of events repeats itself but with reversed signs. In this view, ENSO is a low-frequency basin-wide mode of oscillation which is perfectly predictable. Many factors, however, may limit the predictability of ENSO. Hypothesized mechanisms include random noise [*Kleeman and Power*, 1994; *Penland and Sardeshmukh*, 1995; *Eckert and Latif*, 1997; *Kleeman and Moore*, 1996; *Blanke et al.*, 1997], nonlinear interactions with the annual cycle [*Muennich et al.*, 1991; *Jin et al.*, 1994; *Tzipermann et al.*, 1994; *Chang et al.*, 1994; *Jin et al.*, 1996], or decadal variations in the mean state [*Balmaseda et al.*, 1995; *Kleeman et al.*, 1996; *Latif et al.*, 1997].

The zonal asymmetries in the mean state of the equatorial Pacific Ocean result in a characteristic space-time structure of the ENSO-related anomalies in certain key quantities [see also *Neelin et al.*, this issue]. Both the observations and models show that while SST and surface wind stress are dominated by standing components, the upper ocean heat content (which reflects the dynamical adjustment of the upper ocean in response to low-frequency wind stress variations) is characterized by a propagating mode. Figures 2 and 3 show results from a combined principal oscillation patterns (POP) analysis [*Hasselmann*, 1988] of anomalous monthly SST and upper ocean heat content from the National Centers for Environmental Prediction (NCEP) ocean reanalysis (in which observations were assimilated into an oceanic general circulation model for the period 1982 to 1992) and surface wind stress anomalies from the Florida State University (FSU) data set.

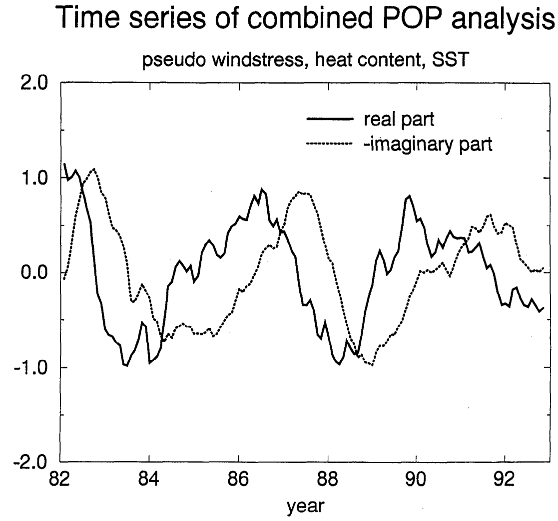

Figure 2. Principal oscillation pattern (POP) coefficient time series of the leading POP mode derived from a POP analysis of a combined data set of observed anomalous SST, upper ocean heat content, and surface wind stress for the period 1982–1992. The data were normalized by their local standard deviation prior to the POP analysis. The leading POP mode accounts for about 32% of the combined variance, the rotation period amounts to about 4 years, and the decay time amounts to about 3 years.

The leading POP mode explains about 32% of the variance in the combined data set and has a rotation period of about 4 years and a decay time of about 3 years. The time period considered for the POP analysis is one that is characterized by a rather regular time evolution, as witnessed by the two POP coefficient time series (Figure 2), and the ENSO prediction skill was relatively high during this particular period (*Ji et al.* [1996]; see also Figure 5, which shows skills from the "Lamont models" for different periods). The two POP coefficient time series vary coherently with a phase difference of about 90° (as theoretically expected) over most of the time, which in itself is an expression of predictability. Notice that after 1991 the amplitude of the POP is reduced and the phase relationship between the two coefficient time series is less obvious. This seems to have had consequences for predictability after this date [see, e.g., *Ji et al.*, 1996].

The leading POP mode is the fundamental ENSO mode from which most forecast models gain most of their predictive potential. The space-time structure of the leading POP mode is largely consistent with the delayed action oscillator scenario. The slow eastward propagation in the equatorial heat content anomalies is clearly seen in the sequence of POP patterns (Figure 3). In order to aid the interpretation of the POP results we show the real and (negative) imaginary patterns which follow each other according to the "POP clock" (real, negative imaginary, negative real, imaginary, and real parts). Equatorial heat content anomalies (reminiscent of Kelvin wave packets) of the same sign (Figure 3a) precede major SST anomalies in the eastern equatorial Pacific (Figure 3d) by a quarter of the rotation period, i.e., about 1 year. The warming

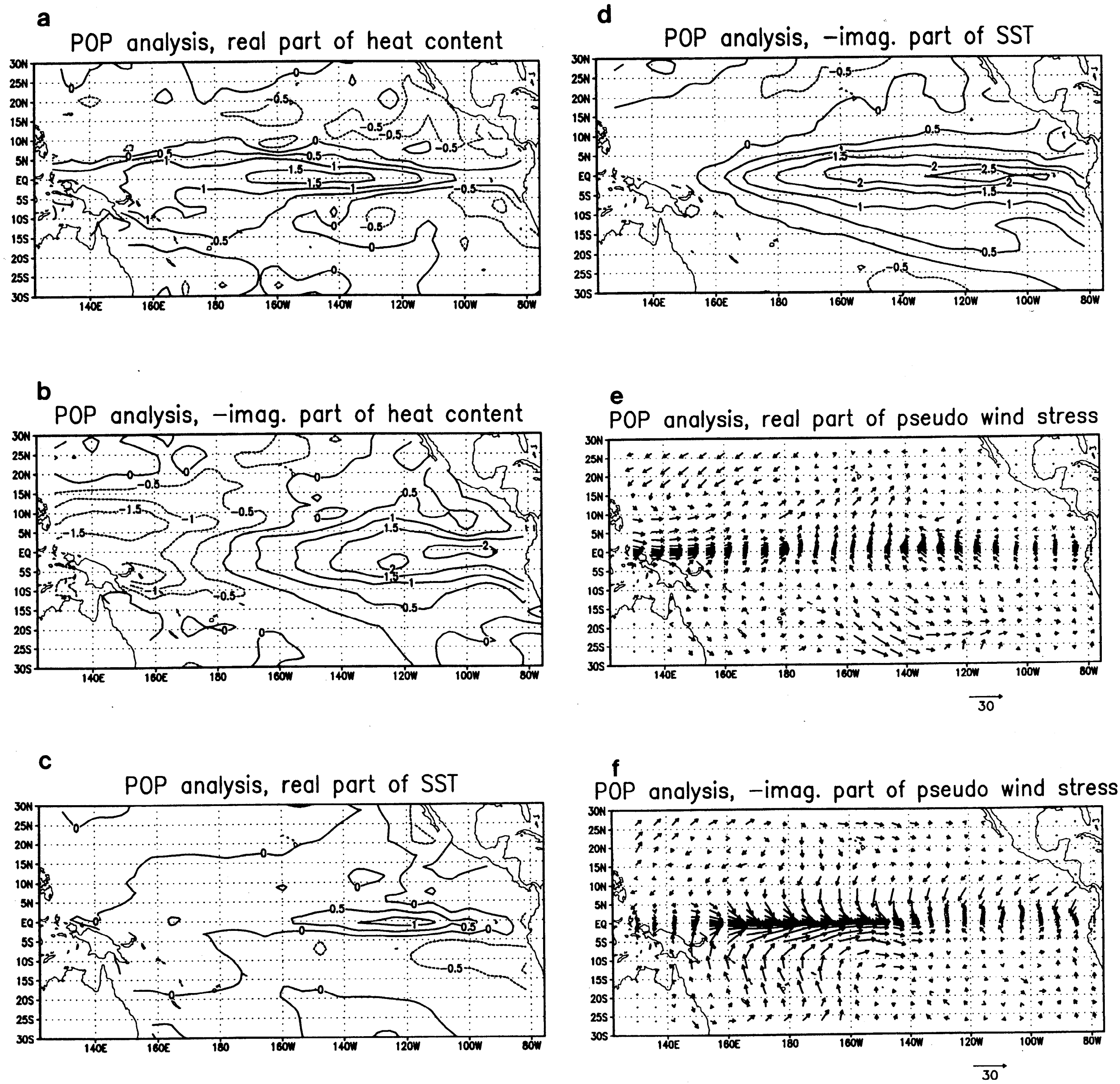

Figure 3. POP patterns of the leading POP mode. Shown are the real and (negative) imaginary parts which follow each other by a quarter of the rotation period, i.e., 1 year. (a) Real part of anomalous heat content, (b) (negative) imaginary part of anomalous heat content, (c) real part of anomalous SST, (d) (negative) imaginary part of SST, (e) real part of anomalous surface wind stress, and (f) (negative) imaginary part of anomalous surface wind stress. Values are normalized.

in the east is accompanied by westerly wind stress anomalies (Figure 3f) and negative heat content anomalies to the west (Figure 3b). The latter are strongest off the equator and are reminiscent of Rossby wave packets which will eventually cause the phase reversal, as described above. In contrast, the anomalous surface stress and SSTs are dominated by standing components. The surface wind stress anomalies, however, show some weak indication of eastward propagation too. Anomalous conditions after 1991 evolved rather differently and did not project well onto the leading ENSO mode [*Kleeman et al.*, 1996; *Latif et al.*, 1997; *Ji et al.*, 1997] and were not well predicted by most forecast models. A discussion of this behavior is given below.

Lau [1985] performed a series of illuminating numerical experiments with the Geophysical Fluid Dynamics Laboratory (GFDL) atmospheric GCM (AGCM). The first experiment, in which climatological SSTs were specified as lower boundary conditions, was successful in reproducing the statistics of the interannual atmospheric variability in midlatitudes with reasonable accuracy but failed to simulate any significant interannual variability in the tropics. The second experiment was a repetition of the first one, except that observed monthly SSTs for the period 1962–1976 were used in the tropical Pacific. This simulation reproduced the observed ENSO-related interannual variations (although the model somewhat underestimated their amplitudes). A third experiment, identical to the second except for different initial conditions, reproduced the low-frequency fluctuations of the second experiment accurately, even though there were significant differences at high frequencies on timescales less than several months. The principal result from these calculations is that low-frequency variability in the tropics does not arise from instabilities of the atmospheric circulation, which would limit its predictability to about 2 weeks, but arises primarily from slow variations in the boundary conditions, specifically the SST. Thus the interannual fluctuations of the tropical atmosphere are predictable to the extent that the low-frequency variations in SST are predictable.

The low-frequency variations in tropical Pacific thermocline and SST, on the other hand, were shown to be reproducible by ocean models, provided the surface wind stress variations are specified from observations [e.g., *Busalacchi et al.*, 1983; *Philander and Seigel*, 1985; *Latif*, 1987; *Wakata and Sarachik*, 1991]. Thus low-frequency variations in both the atmosphere and ocean are strongly controlled by changes in the boundary conditions of the respective other component, which demonstrates the coupled nature of ENSO. Coupled ocean-atmosphere models were developed subsequently in order to gain more insight into the dynamics and predictability of ENSO (e.g., the intermediate coupled model of *Zebiak and Cane* [1987] and the coupled GCM of *Philander et al.* [1992]). The coupled models generally simulate fairly robust ENSO cycles which share many similarities with the observations. In particular, the models simulate realistically the slow evolution in the equatorial heat content, which is so crucial to ENSO predictability (see, for instance, the review paper by *Neelin et al.* [1994] and references and discussions in the review paper by *Battisti and Sarachik* [1995]).

3. Statistical Prediction Models

A hierarchy of ENSO prediction models was developed. The models can be categorized into purely statistical models, which are described in this section, and coupled ocean-atmosphere models, which will be described in the next section. We describe in the following sections only a subset of the models. We have tried, however, to include all models in the reference section or at the internet address http://www.atmos.washington.edu/tpop/pop.htm.

Advanced statistical techniques have increasingly been used during the last few years to identify the principal modes of climate variability on different space scales and timescales. These statistical methods can also be exploited for climate predictions [e.g., *Davis*, 1977; *Barnett and Hasselmann*, 1979; *Hasselmann and Barnett*, 1981; *Barnett and Preisendorfer*, 1987]. The task in statistical prediction is to find an optimal set of precursors (predictors) that predicts best the future evolution of a certain quantity (predictand). However, in constructing statistical prediction schemes one has to find a trade-off between statistical significance and skill. None of the data records used in ENSO prediction schemes go back earlier than 1950, so only a few realizations of ENSO extremes are captured. In the models presented below, care has been taken to avoid artificial skill. However, it should be noted that artificial skill remains a problem in all statistical forecast schemes. Furthermore, the success of statistical forecast schemes does not always imply a causal relationship. In contrast, physical models are less seriously affected by this problem, since model parameters are difficult to tune and generally constrained by physical laws or observations. Moreover, those model parameters that can be picked freely are typically not chosen at the values that are best for prediction purposes, as they are in statistical models.

3.1. Atmospheric Models

In a series of studies it has been shown that low-frequency variability in global sea level pressure (SLP) exhibits a slowly evolving mode which is clearly associated with the ENSO phenomenon [e.g., *Barnett*, 1983, 1985; *van Loon*, 1984; *van Loon and Shea*, 1985; *Graham et al.*, 1987a; *Xu and von Storch*, 1990; *Barnett et al.*, 1991]. As shown by *Barnett et al.* [1991], for instance, this mode involves a slow eastward propagation of SLP anomalies from the Indian Ocean to the eastern tropical Pacific. Atmospheric general circulation models (AGCMs) also simulate this characteristic propagation when forced by observed SSTs [*Barnett et al.*, 1991], and it is this slow evolution in the atmosphere which is exploited by most of the statistical prediction schemes that use atmospheric quantities as predictors. An alternative approach based on a univariate time series, the Southern Oscillation Index (SOI), using singular spectrum analysis was developed by *Kepenne and Ghil* [1992]. This, however, does not mean that the memory of the coupled system resides in the atmosphere, and there is some consensus that the ocean memory provides the long timescale in the coupled system, as discussed in section 2.

Several explanations have been offered for the observed low-frequency variability in sea level pressure. Here only one is described briefly, which assigns the extratropics an active role. It is based on an interaction of land surface processes and the hydrological cycle over Eurasia with the monsoon circulation and the Pacific trade wind field [*Barnett et al.*, 1989]. Heavier than normal snow cover over Eurasia reduces the warming of the continent in summer due to the combined effects of snow, soil, and atmospheric moisture, thus leading to a weakening of the Indian summer monsoon [*Hahn and Shukla*, 1976]. The remote response associated with this perturbation involves also a weakening of the western Pacific low-pressure system, which results in a weakening of the trade winds and the occurrence of persistent westerly surface wind anomalies in this region. It has been speculated that these wind stress anomalies may initiate warm ENSO extremes.

The low-frequency variations in sea level pressure have been used in several statistical prediction studies as predictors for the future development of the ENSO cycle [*Graham et al.*, 1987a, b; *Barnett et al.*, 1988; *Xu and von Storch*, 1990; *Barnston and Ropelewski*, 1992]. Here we show only results from the scheme of *Barnett et al.* [1988] (canonical correlation analysis (CCA)) and *Xu and von Storch* [1990] (POP). The scheme of *Barnston and Ropelewski* [1992] is very similar to the *Barnett et al.* [1988] CCA technique [*Hotelling*, 1935; *Barnett and Preisendorfer*, 1987; *Graham et al.*, 1987a, b; *Barnett et al.*, 1988], which identifies the dominant patterns in each of the two data sets which are most highly correlated.

As predictors, the time history of 1 year of the SLP anomaly field is used. The predictand is an area average of SST anomalies over the "SST 3" region (5°N–5°S, 170°–120°W), and predictions are made on a seasonal basis for the period 1970 to 1989. The results of the predictions (Figure 4) have been cross validated in the sense that the statistical model was developed using data from a time period which was excluded from (and

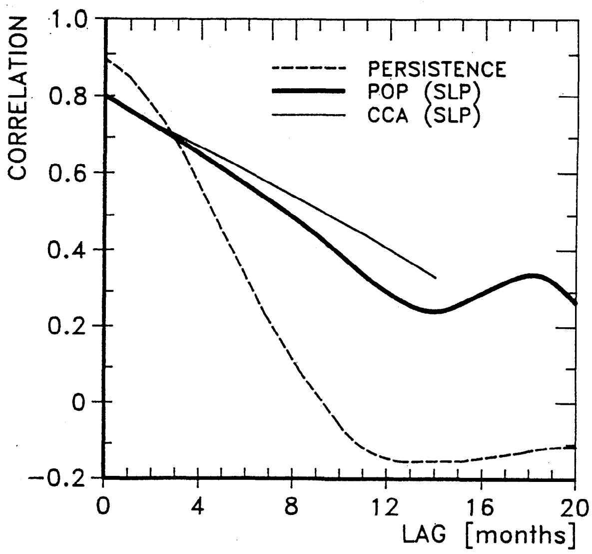

Figure 4. Correlation skill as function of the forecast lag (months) of the statistical ENSO forecast models that use sea level pressure (SLP) as predictors. The canonical correlation analysis (CCA) model (thin line) is based on seasonal predictions of SST anomalies averaged over the "SST 3" region. Correlations for this model are drawn at the center of a particular season. The principal oscillation pattern (POP) model (thick line) is based on monthly predictions of the Southern Oscillation Index (SOI). For reference, also shown is the persistence of a slightly smoothed version of the SOI (dashed line). From *Latif et al.* [1994]; copyright Springer-Verlag.

essentially uncorrelated with) the prediction time period (see *Graham et al.* [1987a, b] for further details). The results can therefore be regarded as true "forecast skills." The CCA model gives significantly better results than the persistence forecast at lead times longer than one season. If one adopts a threshold value for the anomaly correlation of 0.5 for useful predictions, the CCA model has useable skill out to three seasons. As pointed out by *Barnett et al.* [1988], the success of the CCA model at lead times longer than two seasons is due to SLP variations outside the tropical Pacific, which emphasizes the global nature of ENSO. However, this result does not necessarily imply a causal relation as it is possible that SLP changes over the Indian Ocean are a detectable response to ocean-atmosphere interactions in the Pacific sector, as shown by *Latif and Barnett* [1995].

Similar results were obtained from the prediction scheme of *Xu and von Storch* [1990], which relies on the phenomenon being cyclic. This scheme is based on the technique of principal oscillation patterns (POPs). The POP method was also used by *Tang* [1995] to forecast tropical Pacific SST. While *Tang* [1995] used anomalous tropical Pacific (FSU) surface wind stresses, *Xu and von Storch* [1990] designed their POP prediction model to test the "South Pacific Convergence Zone (SPCZ) hypothesis" of *van Loon and Shea* [1985] and therefore use as predictors only SLP variations in the latitude band 15°–40°S. The POP model was not constructed from an independent time period, so its results have to be interpreted with some caution.

As discussed by *Xu and von Storch* [1990], the artificial skill in their POP predictions is expected to be small because they only used a single dominant POP mode in their prediction scheme. The skills of the POP model are comparable to the skills of the CCA model (Figure 4).

We would like to point out that the success of the POP scheme does not imply a causal relationship. In particular, if there are midlatitude impacts of ENSO that lag the peak of ENSO extremes and the ENSO phenomenon is in a quasi-periodic regime (like in the 1970s and 1980s), then the lagged midlatitudinal anomalies that are caused by ENSO extremes will also appear to be precursors of the next ENSO extreme, even if they have no impact back to the tropical Pacific.

3.2. Oceanic Models

White et al. [1987] and *Latif and Graham* [1992] used the outputs of wind-driven ocean models to derive predictors of ENSO. *Latif and Graham* [1992] used the output of an OGCM forced by observed wind stresses to predict tropical Pacific SST by "extended CCA." Time evolutions of temperature anomalies in vertical sections along certain latitudes were used as predictors. *Latif and Graham* [1992, p.] state: "Off-equatorial heat content anomalies at 5°N are shown to contribute significantly to the predictability at these (6–12 months) lead times, while those at 12°N do not." *White et al.* [1987] hypothesize that it is the variability at 12°N (and not 5°N) that is important as a predictor, which is not correct as discussed, for instance, by *Wakata and Sarachik* [1991]. Clearly, the results of *Latif and Graham* [1992] concerning the importance of off-equatorial heat content anomalies are not consistent with those of *White et al.* [1987]. The *White et al.* [1987] scheme suffers from exactly the same problem noted above: The subtropical heat content anomalies are the lagged response to a quasiperiodic ENSO; thus, the subtropical thermal anomalies that are generated by ENSO appear also to lead ENSO, but they are irrelevant to its future evolution.

If the wind stresses over the tropical Pacific (which drive the OGCM), in place of the temperature anomalies, are used as predictors in the statistical prediction scheme, no skill was obtained at lead times longer than a few months. This indicates that the role of the ocean as a complicated integrating space-time filter of the driving wind stresses is essential for achieving skillful ENSO predictions. If the ocean model was linear, a linear statistical scheme could, in principal, also derive the necessary information directly from the wind field. The construction of such a statistical scheme, however, would require very long time series.

Penland and Sardeshmukh [1995] fit a first-order Markov model to the monthly averaged sea surface temperature anomalies from the Comprehensive Ocean-Atmosphere Data Set (COADS), which had been subject to a 3-month running mean and projected onto the leading 20 empirical orthogonal functions (EOFs). Green function matrices for lead times of 1–24 months were estimated on the basis of the equal-time statistics and the lagged covariance matrix estimated at a lead time of 4 months (see *Penland and Sardeshmukh* [1995] for details). Operationally, the predictions are made using real-time marine surface data, provided monthly courtesy of NCEP. Each month, the initial condition thus prepared is operated on by the appropriate Green function matrices to obtain the predictions at different lead times. The method of *Penland and Sardeshmukh* [1995] shows some useful skill out to lead times of about 9 months (not shown).

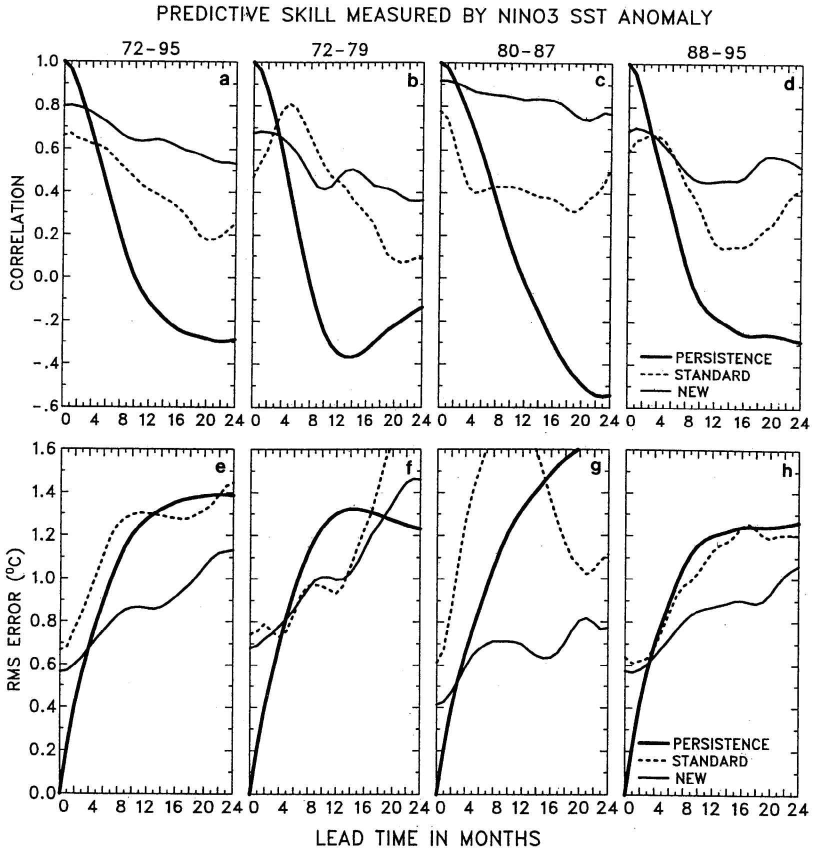

Figure 5. Results in predicting eastern equatorial SST anomalies averaged over the Niño 3 region with the two versions of the Lamont model. (top) Correlation skills; (bottom) root-mean-square (rms) errors. The panels on the very left show the results for the complete period 1972–1995, while the other panels show the results for particular time periods. The results of the standard model are shown as dashed lines, and those for the new model are shown as thin solid lines. The results of the persistence forecast are given by the thick solid lines. Reprinted with permission from *Chen et al.* [1995]; copyright 1995 American Association for the Advancement of Science.

4. Coupled Ocean-Atmosphere Models

Coupled ocean-atmosphere models of different complexity were developed to forecast ENSO-related anomalies. The coupled models can be categorized into three classes of models: intermediate coupled models, hybrid coupled models, and coupled GCMs. Some coupled models employ oceanic data assimilation; others do not. Most coupled models are anomaly models or employ some kind of anomaly coupling (in the case of the coupled GCMs), since climate drift is still a major problem in coupled modelling. Common to all of the intermediate and hybrid coupled models is the explicit assumption that ENSO physics is inherently rooted in the tropical Pacific ocean-atmosphere system.

4.1. Intermediate Coupled Models

A milestone in ENSO forecasting was made soon after the development of the Lamont model [*Zebiak and Cane*, 1987] which is a nonlinear anomaly model of intermediate complexity. The Lamont model has been used routinely in real time for ENSO forecasts since 1986. In particular, it was one of the few real-time forecast models that predicted the onset and evolution of the 1991–1992 warm ENSO phase correctly. The Lamont model has been widely used in prediction and predictability studies [*Cane et al.*, 1986; *Battisti*, 1988; *Goswami and Shukla*, 1991; *Cane*, 1991; *Graham et al.*, 1992; *Chen et al.*, 1995; *Shukla and Kirtman*, 1996]. It is a regional model covering the domain of the tropical Pacific. Thus in this model there is an inherent assumption that the physics associated with all phases of ENSO lies entirely in this region. In stand-alone mode the model simulates realistically the interannual variability in tropical Pacific SST. The mechanism for the interannual variability is associated with the subsurface memory of the system [*Zebiak and Cane*, 1987; *Battisti and Hirst*, 1989] and consistent with the delayed action oscillator scenario.

Two versions of the Lamont model are discussed here. The first one is the original model and will be referred to as the "standard model," while the second one is a relatively new version, which will be referred to as the "new model." Oceanic initial conditions for the standard model are obtained from an uncoupled control integration in which the ocean model is forced by observed (FSU) wind stresses. The atmospheric initial conditions are obtained by forcing the atmospheric model with the SST anomalies simulated by the ocean model in the same control integration. The correlation skill of the standard model for a large ensemble of predictions, initialized monthly during the period 1972–1995 is shown in Figure 5. The correlation drops only very slowly with increasing lead time, and some marginal values are found even at lead times of 2 years. However, more encouraging than the actual level of the correlation at a certain lead time, say at a lead of 1 year, is the slow decrease of skill with increasing lead time. This behavior is markedly different from the purely statistical models, which show a much faster drop in forecast quality (Figure 4). This demonstrates the potential long lead time advantage of coupled models and the inherent limitations in statistical prediction.

However, predictions with the standard model were conducted by initializing the individual model components separately. The only observed information used in the Lamont model is the observed (FSU) surface wind stresses. *Chen et al.* [1995] used the same wind stresses, but they assimilated (nudged) the stresses into the coupled model. This coupled model initialization is referred to as the new model (although the model has not been changed, only the assimilation scheme) and results in remarkably improved skill of the Lamont model (Figure 5). *Chen et al.* [1995] attribute the skill improvement primarily to a reduction of the "initialization shock" and random noise. *Shukla and Kirtman* [1996] attribute the improvement obtained in the new model relative to the standard model to a reduction of the initial error. Although the error growth became slightly stronger in the new model, it did not compensate completely for the reduction in the initial error. There is the potential to improve the forecasts further, since the initial errors are still relatively large (Figure 5). Overall, the study of *Chen et al.* [1995] is promising in view of the development of more complex coupled ocean-atmosphere models. It should be noted, however, that the new model might suffer from some artificial skill, since the nudging parameters used were optimized with respect to the forecast skill.

An intermediate coupled model was developed by *Kleeman* [1993] and differs significantly from the Lamont model in aspects of the coupling, atmospheric convection and heating, and ocean thermodynamics. Recently, the initialization of the coupled model has been improved by using a space-time variational (adjoint) technique to assimilate subsurface thermal data [*Kleeman et al.*, 1995]. This has resulted in a significant increase in the skill of the model relative to the old version that used observed (FSU) wind stresses only to initialize forecasts. The skill levels of the two models (not shown) are comparable to those of the two versions of the Lamont model described above (Figure 5).

4.2. Hybrid Coupled Models

A widely used class of coupled models are "hybrid coupled models" (HCMs), which consist of physical ocean models coupled to empirically derived atmosphere models [*Latif and Flügel*, 1991; *Barnett et al.*, 1993; *Balmaseda et al.*, 1994; *Davey et al.*, 1994; *Wu et al.*, 1994]. Two HCMs, those of *Barnett et al.* [1993] and *Balmaseda et al.* [1994], are now used routinely in real time to forecast tropical Pacific SST anomalies. In hybrid coupled models the atmosphere's response to variations in the oceanic boundary conditions is expressed by a statistical (empirical) model inferred from data. The use of statistical atmosphere models can be justified, because at low frequencies the atmosphere over the tropical Pacific can be regarded as a strongly forced quasi-equilibrium system governed by the state of tropical Pacific SST. ENSO theory [see *Neelin et al.*, this issue], observations (e.g., Figure 3) and studies with coupled ocean-atmosphere general circulation models support this view [e.g., *Philander et al.*, 1992; *Latif et al.*, 1993a]. Since the empirical atmosphere models are derived from data, they can simulate the full atmospheric feedback loop. However, because the atmosphere is assumed to have no inertia, the memory of a coupled system consisting of such a "slave" atmosphere and a dynamical ocean model resides entirely in the ocean.

Before we continue the discussion of the HCMs we describe briefly one of the earliest ENSO prediction models, the one of *Inoue and O'Brien* [1984], in which the atmospheric feedback is assumed to be constant. This scheme is based on a linear reduced gravity ocean model that successfully simulates variations in thermocline depth or sea level in the tropical Pacific [*Busalacchi et al.*, 1983]. In the predictive mode the ocean model is forced by observed (FSU) wind stress anomalies up the prediction start time. Thereafter the wind stress anomaly is held constant, while the ocean evolves freely. On the basis of a number of case studies the scheme showed skill at 3 months and was a useful scheme for forecasting the onset of major extremes in the ENSO cycle as well as the demise of warm events. Since the *Inoue and O'Brien* [1984] scheme does not carry SST and SST has relatively high persistence at 3-months lag and the reduced gravity model was used to predict the thermocline field only 3 months in advance, there is some discussion about the meaning of the results.

At longer lead times, changes in the atmospheric feedback become important. *Latif and Flügel* [1991] were the first to make ENSO forecasts using an empirical atmosphere model coupled to an OGCM. In this model the anomalous surface wind stress at a given grid point was expressed only in terms of the local SST anomaly. The seasonal variation of the feedback was not taken into account. Although this coupled model showed marginal skill at lead times up to about 1 year in perfect model experiments, the model has low forecast skill using realistic initial conditions.

Graham et al. [1992] coupled the oceanic component of the coupled model of *Zebiak and Cane* [1987] to an empirical atmospheric model. They determined the atmospheric feedback from a regression analysis of SST and wind stress anomalies in EOF space so that remote influences in the SST anomaly field could be taken into account. Furthermore, the statistical model accounts for the seasonal dependence of the feedback by using different models for each month. Most subsequent hybrid coupled model developments adopted a similar strategy. The details in deriving the empirical atmosphere models, however, can differ among the models. The models of *Balmaseda et al.* [1994], *Davey et al.* [1994], and *Wu et al.* [1994], for instance, use the technique of "associated patterns" instead of EOFs.

The hybrid coupled models yield generally useful ENSO predictions for lead times up to about 1 year. That is, the anomaly correlation coefficient between observed and predicted SST anomalies averaged over the Niño 3 region, for instance, amount to values above 0.5 at lead times of 1 year (not shown). Here we show some results of the *Barnett et al.* [1993] HCM (Figure 6), which was the first hybrid model used routinely in real time. The model has an OGCM coupled to a statistical (EOF) atmosphere that was derived using the same procedure as applied by *Graham et al.* [1992]. The hybrid coupled model exhibits substantial correlation skill even at lead times of 12–18 months in the central tropical Pacific (Figure 6). This is an important region in forcing extratropical circulation anomalies, and this was exploited in the two-tiered approach, which is described below.

4.3. Coupled GCMs

The most complex models applied to ENSO forecasting are coupled ocean-atmosphere general circulation models

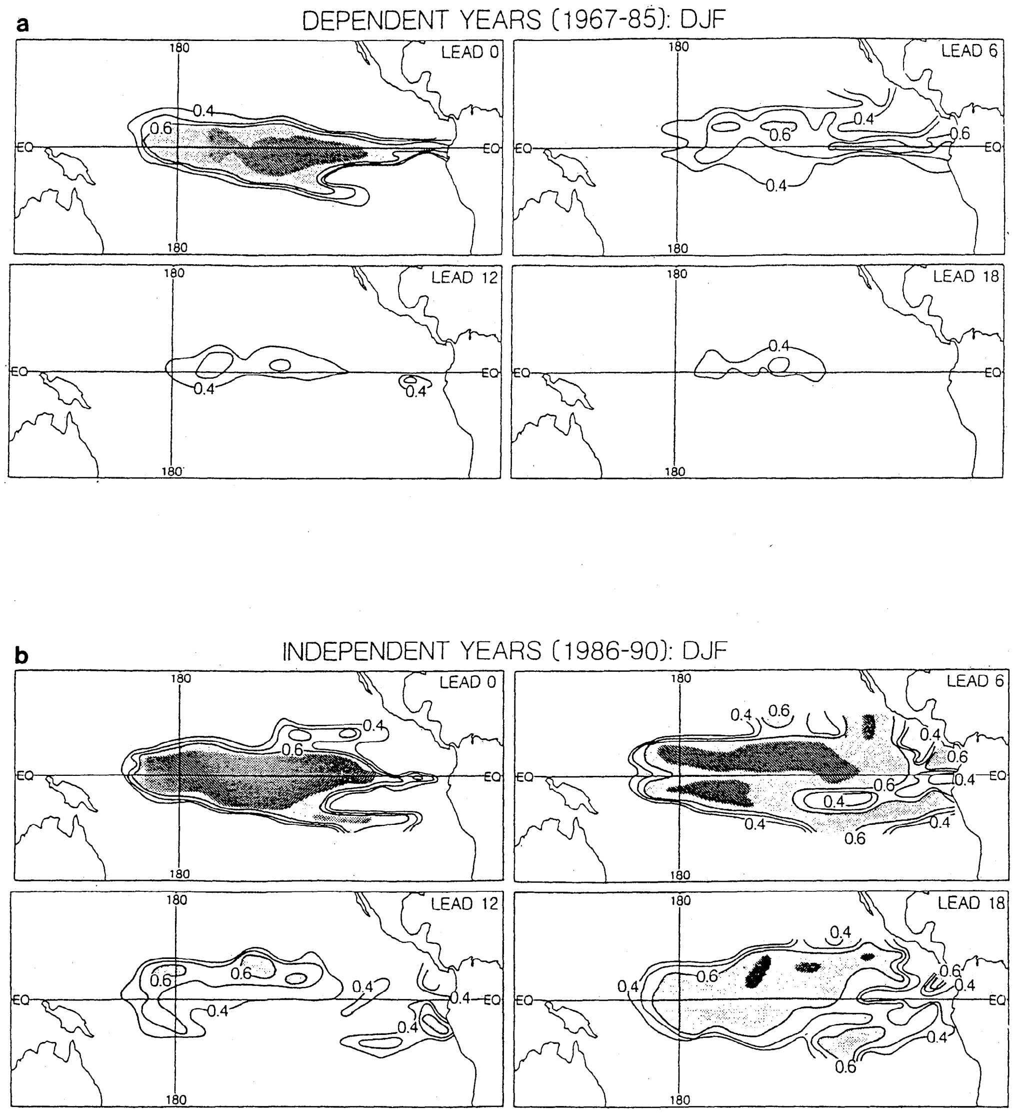

Figure 6. Correlation skills of the *Barnett et al.* [1993] hybrid coupled model (HCM). Shown are the results of forecasts predicting winter (December-January-February) SST anomalies. The results for the "dependent" period 1967–1985, which was used to derive the statistical atmosphere model. The correlations for the "independent" period 1986–1990, which was not used in the construction of the atmosphere model. From *Barnett et al.* [1993].

(CGCMs). However, since climate drift is still a major problem in many CGCMs, most of them make use of some kind of anomaly coupling or anomaly initialization. The CGCM of *Latif et al.* [1993a] was the first coupled GCM that was applied successfully to ENSO predictions [*Latif et al.*, 1993b]. It consists of a high-resolution ocean model extending over all three oceans and a global low-resolution (spectral resolution of T-21) atmosphere model. The two models exchange information within the region 30°N to 30°S and are coupled without any flux correction. The coupled GCM simulates realistically the ENSO cycle in an extended-range control integration. As in most coupled models and consistent with observations, the subsurface memory of the coupled system plays an important role for the interannual variability [*Latif et al.*, 1993a].

For predictions, *Latif et al.* [1993b] initialize their CGCM as follows. The ocean model is spun up with observed wind stress anomalies, which are added to the climatological wind stresses simulated in the control integration with the coupled model. Thereafter the atmospheric model is forced by the ocean model's SST for 1 month. This procedure minimizes the "climate drift" problem. Predictions were initialized for the warm periods of 1972–1973, 1982–1983, and 1986–1987 and for the cold periods of 1973–1974 and 1988–1989. Each period was predicted using four sets of different initial conditions separated by 3 months. The CGCM is successful in predicting the observed changes in SST in the Niño 3 region up to lead times of about 1 year (Figure 7), as was inferred from the anomaly correlations (not shown). Only "events" were chosen for the prediction experiments, however, so the results should be treated with considerable caution.

Another CGCM for the use in seasonal forecasting was developed by *Kirtman et al.* [1996], hereafter referred to as the "Center for Ocean-Land-Atmosphere Studies (COLA) model." This model (which is now used routinely in real time) consists of a high-resolution regional Pacific basin ocean model coupled to the global COLA AGCM run at a spectral resolu-

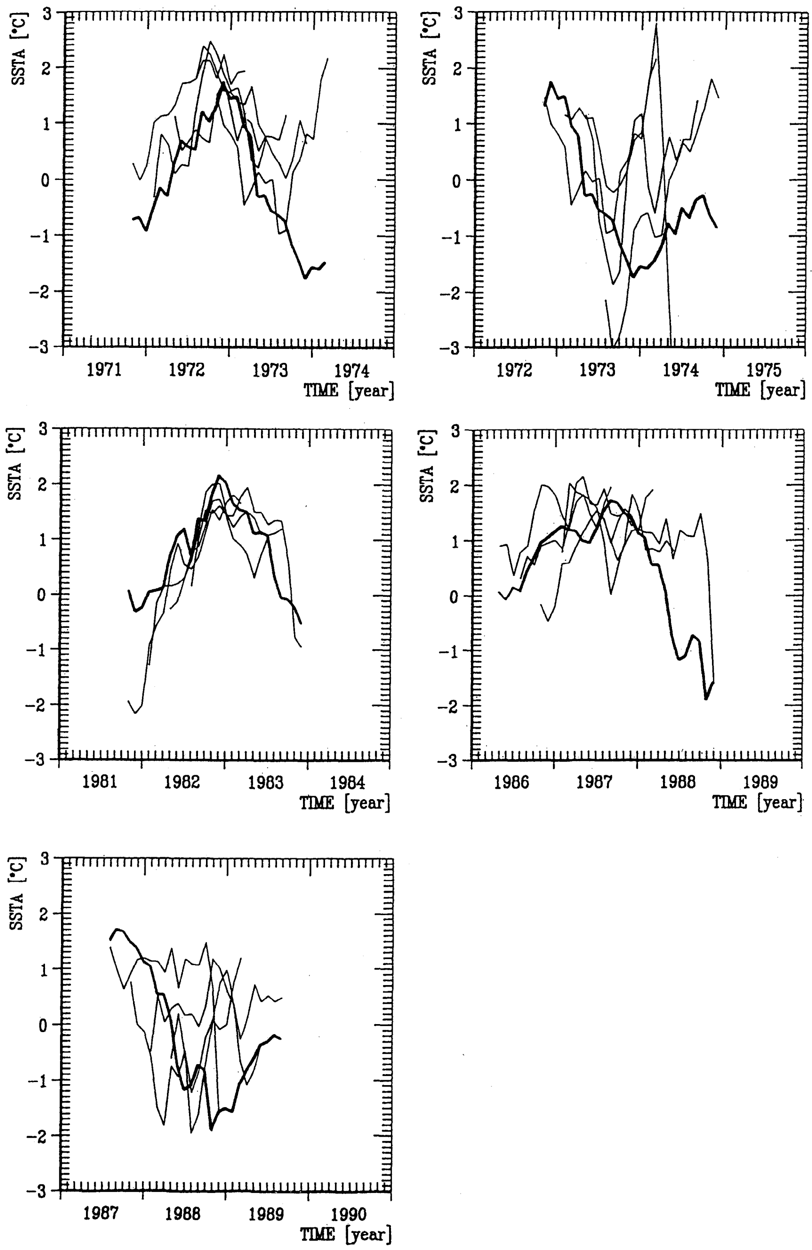

Figure 7. Individual predictions (thin lines) of SST anomalies (degrees Celsius) averaged over the SST 3 region conducted with the coupled general circulation model (CGCM) of *Latif et al.* [1993a]. Shown are the results for three warm (1972–1973, 1982–1983, and 1986–1987) and two cold events (1973–1974 and 1988–1989). The thick lines in each panel show the observed SST anomalies. The individual predictions have a duration of 16 months. From *Latif et al.* [1993b].

tion of T-30. In developing ocean initial conditions an iterative procedure that assimilates the zonal wind stress anomaly based on the simulated sea surface temperature anomaly error is applied. The COLA model employs anomaly coupling with surface zonal wind stress anomalies determined empirically from the AGCM 850-hPa zonal wind anomalies. The model was applied to a large ensemble of ENSO predictions. The resulting correlation skill (Figure 8) attains values larger than 0.6 over a sizeable region of the tropical Pacific for lead times of 1 year and is comparable to those of other coupled models.

However, as in the Lamont model, the CGCMs of *Latif et al.* [1993b] and *Kirtman et al.* [1996] used only observed (FSU) surface wind stresses to initialize predictions. Efforts at the Geophysical Fluid Dynamics Laboratory (GFDL) and National Centers for Environmental Prediction (NCEP) have succeeded in developing integrated forecasting systems by combining sophisticated ocean data assimilation schemes with CGCMs in order to make use of the ocean measurements that have become increasingly available (see also *McPhaden et al.* [this issue], who describe, for instance, the "Tropical Atmosphere-Ocean" (TAO) array). While the effort at GFDL is experimental in nature, two versions of the NCEP CGCM are used routinely in real time in forecast mode.

The GFDL scheme [*Rosati et al.*, 1997] consists of an atmosphere model run at a spectral resolution of T-30 resolution which is coupled to a 1° × 1° global ocean model. The merid-

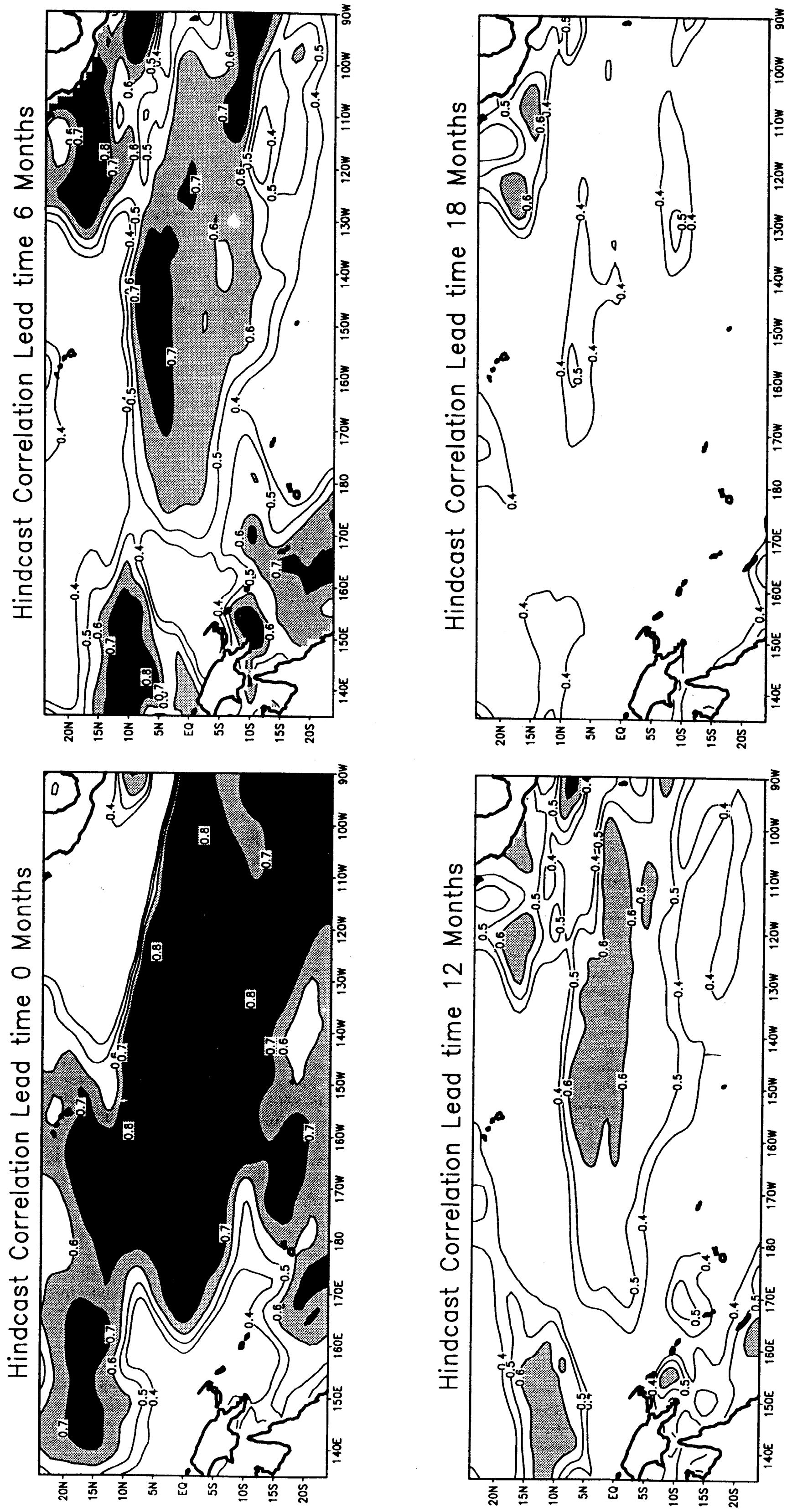

Figure 8. Hindcast correlations of the Coupled Ocean-Land-Atmosphere Studies (COLA) prediction system for an ensemble of 120 predictions. The initial conditions for the ensemble are chosen from all seasons in the period 1964–1991.

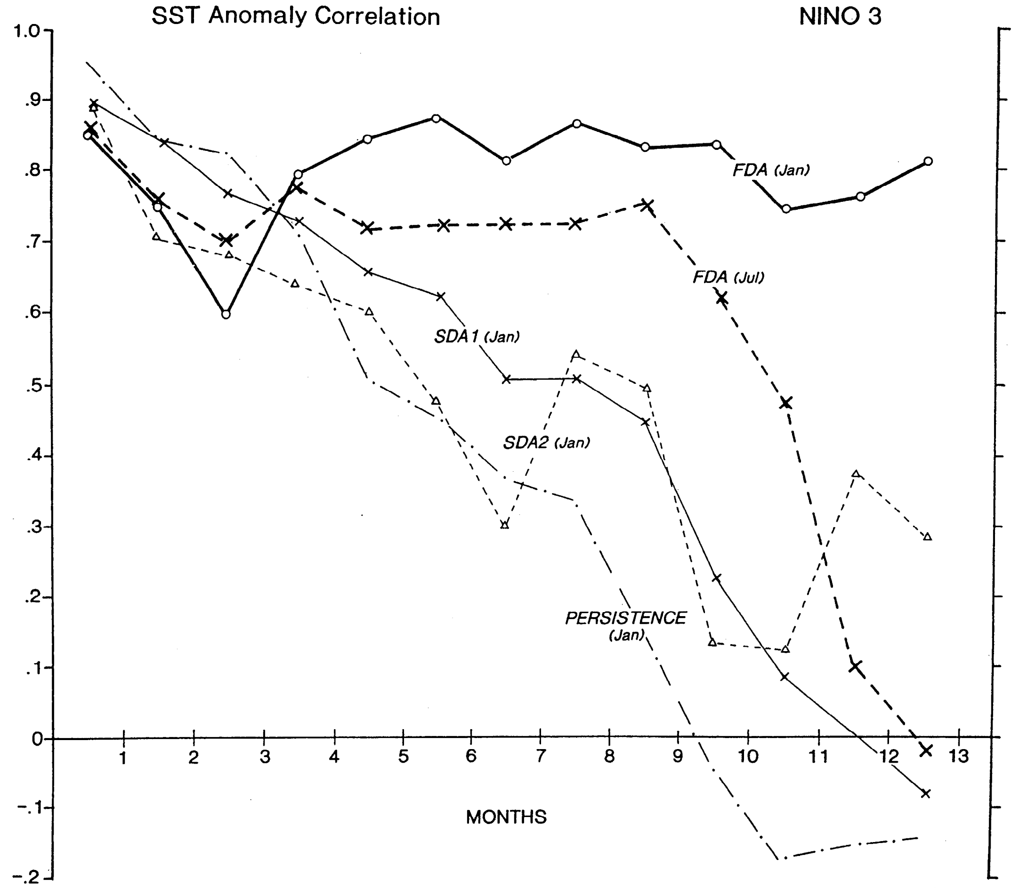

Figure 9. Results in predicting eastern equatorial SST anomalies averaged over the Niño 3 region with the three versions of the Geophysical Fluid Dynamics Laboratory (GFDL) CGCM. Correlation skills are shown for predictions starting in January and July. The lines labeled "FDA" denote the correlations obtained with the full (variational) assimilation scheme used to assimilate three-dimensional temperatures. The lines labeled "SDA1" denote the correlations obtained when SSTs and surface stresses are nudged, while those labeled "SDA2" denote the correlations obtained when SSTs only are nudged to the coupled model. From *Rosati et al.* [1997].

ional resolution of the ocean model, however, increases to 1/3° within the region 10°N–10°S. Atmospheric initial conditions are obtained from the National Meteorological Center (NMC), while the oceanic initial conditions were obtained applying three different data assimilation schemes, two nudging schemes and one "full" (variational) scheme [*Derber and Rosati*, 1989]. The nudging schemes were applied to the coupled model, while oceanic initial conditions were obtained in uncoupled mode using the variational method. SSTs were used in one nudging scheme, while SSTs and surface wind stresses were used in the other nudging scheme. Three-dimensional temperature fields constructed from different sources were assimilated in the case of the "full" data assimilation scheme [*Rosati et al.*, 1995].

Rosati et al. [1997] made forecasts starting either in January or July for the period 1982–1988, which yields ensembles of seven members only for each calendar month. The results indicate that data assimilation is crucial in obtaining skillful forecasts. The oceanic initial states were very different in the three cases, and a comparison of the forecast results obtained from the three different sets of initial conditions revealed that the most skillful forecasts were obtained by assimilating subsurface observations (Figure 9). *Rosati et al.* [1997] hypothesized that the subsurface data correct for the tendency of the ocean model to simulate a too diffusive thermocline. This tendency could alter the response of the SST to thermocline changes since the subsurface would be disconnected from the surface in the case without subsurface temperature assimilation.

Three versions of the NCEP CGCM (CMP6, CMP9, and CMP10) have been developed over the last few years, which differ mainly in the treatment of the surface heat flux [*Ji et al.*, 1994a, b; *Ji and Leetmaa*, 1997; *Ji et al.*, 1996]. All models use a high-resolution Pacific basin OGCM coupled to a modified version of the NMC's operational weather forecasting model that is run at a spectral resolution of T-40. A full ocean data assimilation system by which the three-dimensional temperature observations are assimilated is used, similar to that of *Rosati et al.* [1995].

Forecast skills for tropical SST anomalies are estimated through 1-year hindcast experiments initialized monthly from October 1983 through April 1994 for the CMP6 model and from May 1982 through April 1994 for the other two models. All three models yield similar skills in the central equatorial Pacific, while the two later versions (CMP9 and CMP10) perform considerably better in the eastern equatorial Pacific (Figures 10a and 10b). Skillful forecasts are obtained up to lead times of about three seasons. As did *Kleeman et al.* [1995] and *Rosati et al.* [1997], *Ji and Leetmaa* [1997] emphasize the im-

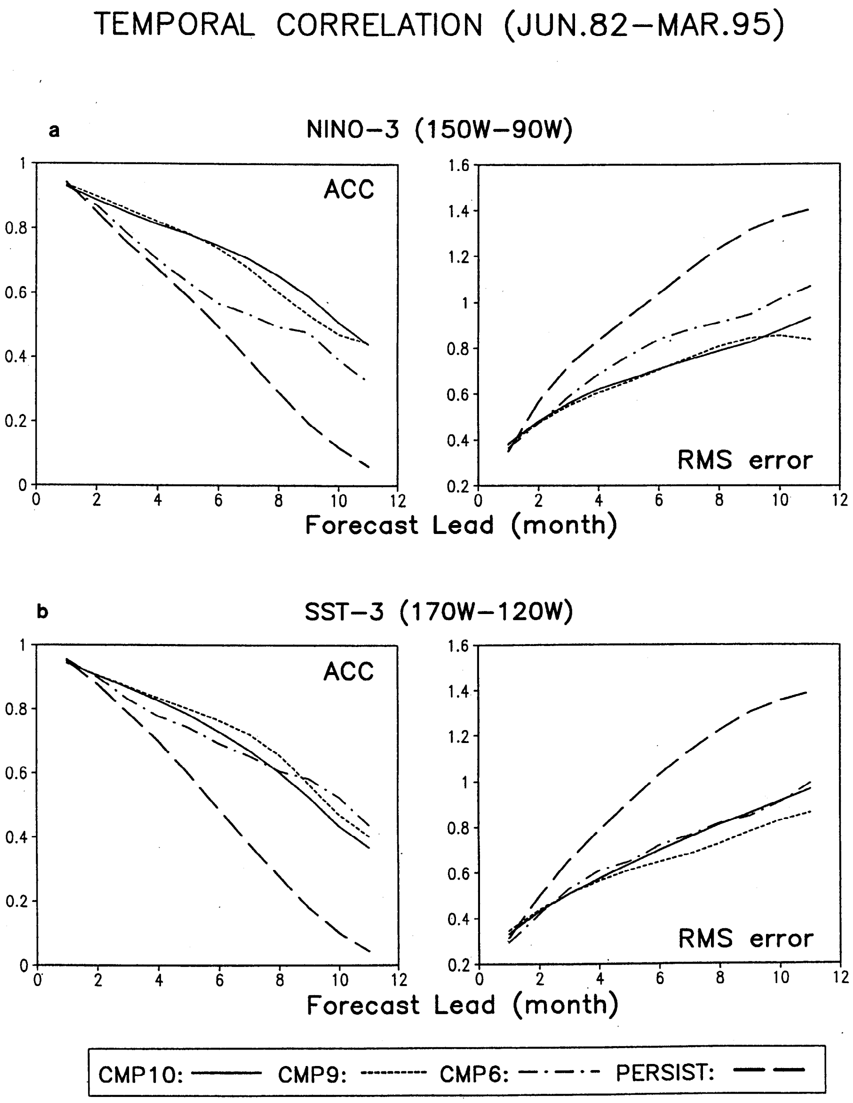

Figure 10. Results in predicting equatorial SST anomalies with different versions of the NCEP CGCM (CMP6, CMP9, and CMP10). (a) Correlations and root-mean-square (rms) errors for the Niño 3 region; (b) same as Figure 10a, but for the SST 3 region; and (c) same as Figure 10b, but when different data sets are assimilated. Best results are obtained when the Tropical Atmosphere-Ocean (TAO) data are assimilated in addition to the expendable thermograph (XBT) data (F-RA2), while the results are degraded when the TAO data are neglected (F-NTAO). Worst results are obtained when no data are assimilated (F-HFSU). From *Ji et al.* [1996] and *Ji and Leetmaa* [1997].

portance of data assimilation to get realistic forecasts of tropical Pacific SST. In particular, it was shown that the use of the TAO data yielded the better forecast results, relative to the cases in which only expendable bathythermograph (XBT) data or wind stresses were used (Figure 10c). *Ji et al.* [1996] note also a marked decadal variation in skill, with considerably lower skill levels in the 1990s relative to the 1980s, a result which was also found by *Chen et al.* [1995] (see Figure 5).

5. Forecasts of Teleconnected Anomalies Associated With ENSO

We have restricted ourselves so far to the description of the state of the art in predicting tropical Pacific SST anomalies. It is well known, however, that SST anomalies in the tropics can force significant global climate anomalies [e.g., *Horel and Wallace*, 1981; *Ropelewski and Halpert*, 1989; *Glantz et al.*, 1991; *Trenberth et al.*, this issue]. All CGCMs employ global atmosphere models and have therefore the potential to forecast global climate anomalies that are connected to tropical Pacific SST anomalies.

Most CGCMs, however, suffer still from climate drift. Although we expect that these problems can be overcome in the near future, the quality of climate predictions is limited by the drift. An alternative and more economical approach, the two-tiered approach, was proposed by *Bengtsson et al.* [1993], *Barnett et al.* [1994], and *Hunt et al.* [1994]. Global climate forecasts are obtained in two steps using the two-tiered approach. First, tropical Pacific SST anomalies are predicted with a regional tropical Pacific coupled ocean-atmosphere model. *Bengtsson et al.* [1993] and *Barnett et al.* [1994] used the hybrid coupled model described in work by *Barnett et al.* [1993] (see above). This hybrid coupled model is most successful in pre-

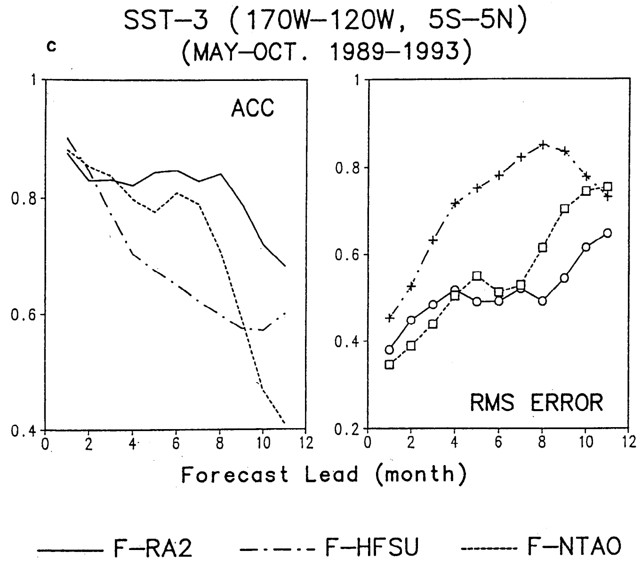

Figure 10. (continued)

dicting central equatorial SST anomalies, and fortunately, these are most important in forcing global climate anomalies. An atmospheric GCM is then forced in the second step by the forecasted tropical Pacific SST anomalies. This yields global forecasts of quantities, such as surface temperature and rainfall. A similar two-tiered approach was applied by *Hunt et al.* [1994], who used tropical Pacific SST anomalies predicted by the Lamont model.

Here we show an example from the paper of *Barnett et al.* [1994]. They chose in a pilot study seven ENSO extreme years (4 warm and 3 cold years) to demonstrate the utility of the two-tiered approach. In order to account for the relatively high internal variability of the atmosphere, ensembles of three members were conducted for each case. It should be noted, however, that much larger ensembles are generally required, as discussed by *Barnett* [1994]. The use of extreme cases only leads certainly to an overestimation of the skill, but it was felt that if the forecast procedure did not work for these large events, then it would likely not work at all. Results are shown for a lead time of two seasons (Figure 11). The two-tiered approach shows not only skill in predicting the large-scale circulation anomalies (as expressed by the 500-hPa height anomalies) over large parts of the globe (Figure 11a) but also the surface temperature and rainfall anomalies over many regions over land (Figures 11b and 11c).

6. Some Skill Sensitivities

We have considered so far only results that represent the overall performance of the forecast models. It is observed, however, that the skill in most forecast models is not constant but varies with season, from decade to decade, and with the phase of the ENSO cycle. These sensitivities are not yet fully understood and are a matter of intense ongoing research. Some hypotheses, however, which may explain the sensitivities at least partly are given below.

6.1. Dependence of Skill on Season

The seasonal dependence in the persistence of tropical Pacific SST anomalies is well established and was described in many papers [e.g., *Wright et al.*, 1988]. The autocorrelation of tropical Pacific SST anomalies attains a minimum in the boreal spring and a maximum in the boreal fall. Many ENSO prediction models show a similar seasonal dependence in skill [*Latif et al.*, 1994], with lowest values in spring [e.g., *Blumenthal*, 1991; *Goswami and Shukla*, 1991; *Latif and Flügel*, 1991; *Latif and Graham*, 1992; *Webster and Yang*, 1992]. We would like to note, however, that it is not clear that the spring barrier in autocorrelation is the cause of the spring barrier in forecast skill.

The reasons for the seasonal dependence in skill are still not fully resolved. Different hypotheses were put forward to explain the "spring predictability barrier," including causes inside

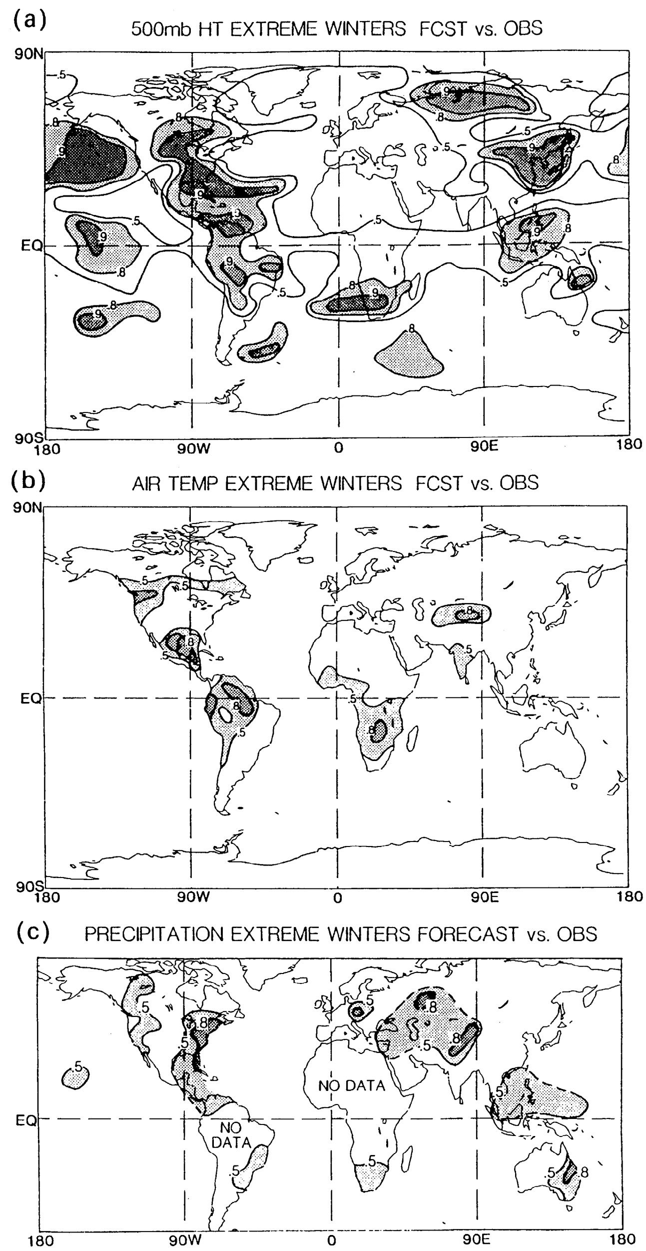

Figure 11. Results in predicting global ENSO-related climate anomalies two seasons ahead using the two-tiered approach. Shown are the correlations obtained for the seven extreme winters chosen. (a) Correlations for the 500-hPa height anomalies, (b) correlations for surface air temperature anomalies over land, and (c) correlations for rainfall anomalies over land. From *Barnett et al.* [1994].

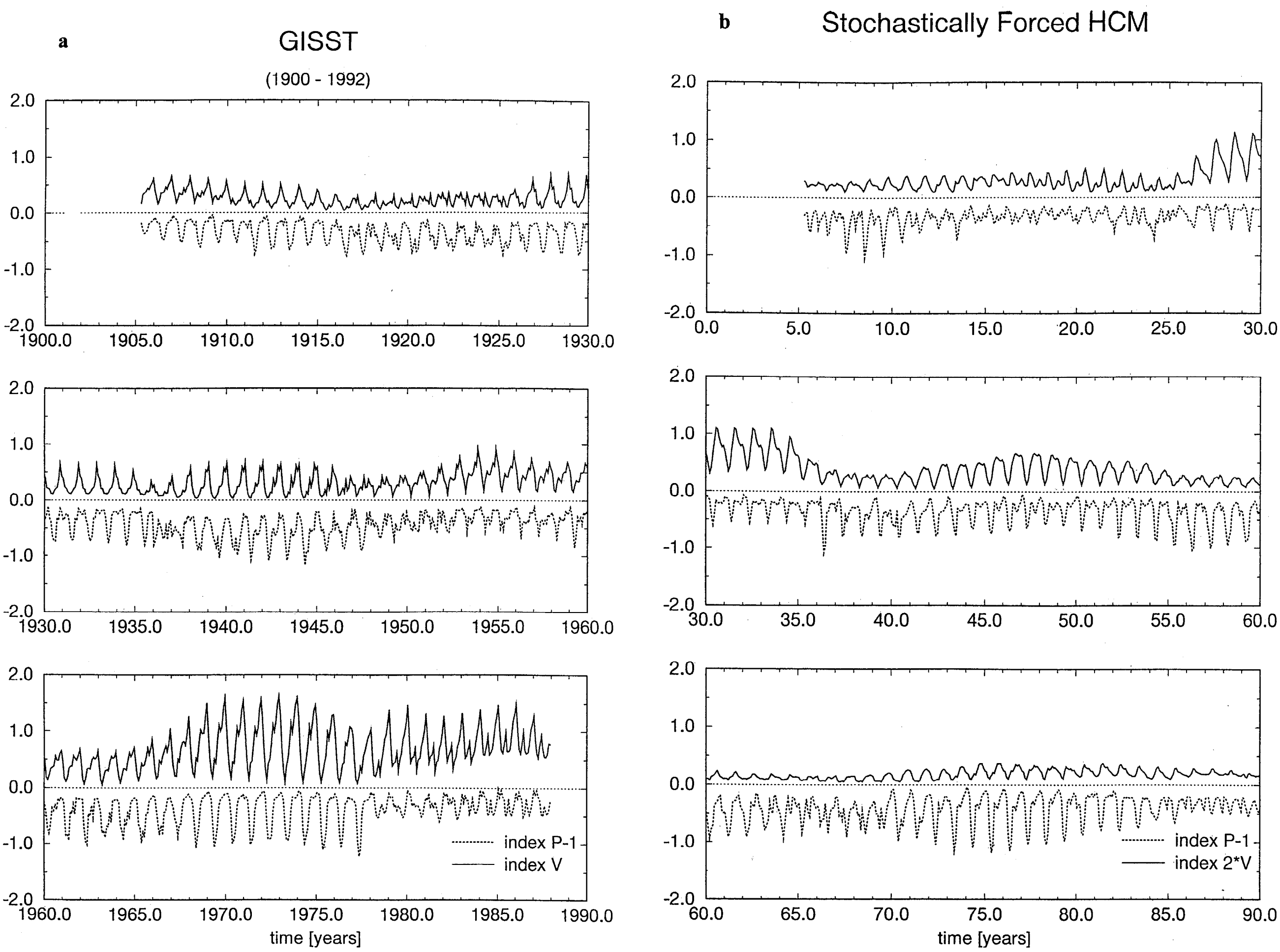

Figure 12. Decadal variations in the 3-months persistence (dashed lines) and variability indices (full lines) as defined by *Balmaseda et al.* [1995]. (a) Results obtained from SST observations (GISST) averaged over the Niño 3 region for the period 1900–1992 (redrawn after *Balmaseda et al.* [1995]. (b) Indices simulated by the stochastically forced hybrid coupled model (HCM) in a 90-year integration.

and outside the tropical Pacific region. *Zebiak and Cane* [1987] and *Battisti* [1988], for instance, discussed the spring predictability barrier in the light of their coupled ocean-atmosphere models and showed that the instability of the system, although favoring growth at any time of the year, is weakest during spring time. They concluded that the predictability should be smallest in spring, because the system loses part of its memory during this season. However, since the system supports unstable growth during the other seasons, the predictability should not be lost completely, because the time during which the growth is small is significantly shorter than the characteristic wave transit time.

An alternative hypothesis was offered by *Webster and Yang* [1992], who relate the spring predictability barrier to interactions of the Pacific trade wind field with the summer monsoon, which is in its strongest growth phase in boreal spring. Recently, however, the spring predictability barrier has been almost eliminated in the latest version of the Lamont model [*Chen et al.*, 1995], suggesting that the spring predictability barrier is not intrinsic to the real climate system and that it may be a problem of the models. The issue of the spring predictability barrier, however, is still a matter of ongoing research.

6.2. Dependence of Skill on Decade

Balmaseda et al. [1995] investigated the autocorrelation of tropical Pacific SST anomalies for many decades (Figure 12a). The minimum in the autocorrelation in boreal spring, the so-called spring predictability barrier was well developed during the 1970s, but virtually absent during other decades. The 1980s, for instance, were highly predictable (see Figure 5) and did not exhibit a strong seasonal dependence in the autocorrelation [*Balmaseda et al.*, 1995]. This is consistent with the studies of *Ji et al.* [1996] and *Chen et al.* [1995], who found that the prediction skill levels during the 1990s were considerably lower relative to the 1980s. In fact, most prediction models exhibit relatively low skills during the 1990s. An example is given in Figure 5, which shows the skills for the Lamont models for particular time periods. This indicates that the existence or nonexistence of the seasonal dependence in the autocorrelation is somehow related to the forecast skill to be expected.

The decadal variations in the persistence of tropical Pacific SST anomalies might be caused by random noise. This is shown in Figure 12b, which displays the results from a stochastically forced hybrid coupled model. The unperturbed HCM simulates a regular ENSO cycle with a period of about 5 years that decays slowly toward the end of the integration. The underlying dynamics of the simulated ENSO cycle is consistent with the delayed action oscillator scenario. The HCM was perturbed by adding spatially coherent noise, which was derived from observations to the mean surface wind stress [*Eckert and Latif*, 1997]. The decadal variations in the persistence of tropical Pacific SST anomalies are strikingly similar to those observed, which suggests that the decadal variations in predictive skill might also result from interactions within the tropical Pacific itself.

A further possible cause of decadal variations is illustrated in the Lamont model and discussed by *Zebiak and Cane* [1991]. They showed that oscillations in their intermediate coupled model are subject to strong variation from decade to decade. The mechanism here appears to be nonlinear interactions within the deep tropical ocean-atmosphere system.

6.3. Dependence of Skill on the Phase of the ENSO Cycle

There is also some evidence that the prediction skill depends on the phase of the ENSO cycle (see, e.g., *Chen et al.* [1997] for a discussion of this issue). It is well known, for instance, that active periods with strong SST anomalies are more predictable than quiet periods with weak SST anomalies, as demonstrated by using the standard Lamont model. Its prediction skill was found to be considerably higher for the 20 "event" cases of *Latif et al.* [1993b] (Figure 7) relative to that of the complete ensemble [*Latif et al.*, 1993b]. A similar result was found by *Wu et al.* [1994]. They showed that forecasts with their hybrid coupled model tended to be more skillful when the initial conditions projected strongly onto the leading (EOF) mode of anomalous SST, so that the future evolution of the model trajectory could be constrained.

7. The Other Two Tropical Oceans

The TOGA program focused mostly on the tropical Pacific because of the predominance of the ENSO phenomenon and because the physics of ENSO is routed in that region. There is, however, also considerable interannual variability observed in the tropical Indian [e.g., *Meehl*, 1987] and Atlantic Oceans [e.g., *Servain*, 1991]. It is still unclear as to what extent these fluctuations are predictable. Part of the interannual variability in these two tropical oceans appears to be forced by ENSO itself through atmospheric teleconnections and amplified by local air-sea interactions. Moreover, strong ENSO extremes seem also to lead occasionally to delayed responses in the equatorial Indian and Atlantic Oceans. Such fluctuations are potentially predictable, as shown by *Latif and Barnett* [1995].

The tropical Indian Ocean SST, for instance, follows closely that of the tropical Pacific, while anomalous cooling (warming) is observed in the equatorial Atlantic during strong warm (cold) extremes in the tropical Pacific. The warm event in the equatorial Atlantic in the year 1984 was probably caused by a delayed response to the record warming 1982–1983 [see, e.g., *Delecluse et al.*, 1994], and it was predictable with a hybrid coupled model at lead times of many months [*Latif and Barnett*, 1995]. Research is continuing in order to determine the relative roles of tropical Indian and Atlantic Ocean SST anomalies in forcing tropical climate anomalies, and there exist some studies which assign non-Pacific SST anomalies an active role in forcing tropical precipitation anomalies [e.g., *Ward and Folland*, 1991]. This issue will be taken up further within the CLIVAR program.

There is room also for internal air-sea interactions, especially in the equatorial Atlantic, which has a similar zonally asymmetric basic state as the equatorial Pacific. *Zebiak* [1993], for instance, describes internal interactions in and over the equatorial Atlantic that are independent of ENSO. The dynamics of the internal Atlantic variability, however, shares many aspects with those underlying ENSO. The relative small basin size of the equatorial Atlantic seems to favor a relatively short oscillation period of about 2 years [*Latif et al.*, 1996]. The internal Atlantic ENSO-like oscillation, however, appears to be much more damped than ENSO itself, which can be also understood in terms of the different basin sizes. It seems therefore likely that the internal Atlantic oscillation is less predictable than ENSO.

8. Discussion

The TOGA program has contributed considerably to the understanding of the ENSO phenomenon in general and its predictability in particular. A hierarchy of ENSO prediction schemes was developed, and operational ENSO predictions several seasons ahead are performed at present with about a dozen of forecast models. Some forecasts were quite successful [e.g., *Kerr*, 1994] and beneficial to the economies of several countries. There are, however, some open questions that need to be addressed in the future in order get more insight into ENSO predictability.

What are the ENSO predictability limits? This question has not been addressed in detail so far. Different factors limiting ENSO predictability have been identified, such as random noise or nonlinearities, but their relative contributions are not yet determined. Estimates of ENSO predictability limits range from a few months to at least a cycle length. Furthermore, the interactions of ENSO with phenomena outside the tropical Pacific need to be addressed in more detail. The interaction of ENSO with the monsoons, for instance, is a matter of intense research, and it is still unknown whether the explicit inclusion of the monsoons and other processes outside the tropical Pacific will enhance the ENSO forecast skill.

As described above, the skill in forecasting ENSO is time and model dependent. In the Lamont model, for instance, the 1980s were highly predictable, while other periods such as the mid-1970s or the 1990s were less predictable. It remains to be shown, however, whether these latter periods are inherently less predictable or whether more complete forecast models that are able to handle decadal variations in the mean state will perform better than anomaly models. *Latif and Barnett* [1994] and *Gu and Philander* [1997] have put forward mechanisms for decadal variability that could feed back onto the tropics. These hypotheses, however, have to be viewed with some caution, since they have not been proven yet by observations. Furthermore, more advanced assimilation techniques might also help to increase the skill during these particular periods. Nevertheless, it is likely that the predictability of the system varies considerably from one decade to the other, and strategies must be developed that help identify which regime we are in. An analogous situation exists in numerical weather prediction. Although it is commonly believed that the overall predictability limit for weather phenomena is of the order of 2 weeks, specific situations (like blocking) can be more predictable.

Techniques of data assimilation and initialization are still at a relatively early stage of development. The different forecast models use rather different initialization procedures, but they yield relatively similar skills. The HCM of *Barnett et al.* [1993], for instance, is initialized with observed SSTs only, while the Lamont models use only observed wind stresses to initialize forecasts. The COLA CGCM uses both of these quantities. The intermediate coupled model of *Kleeman et al.* [1995] assimilates a measure of upper ocean heat content. The coupled GCMs developed at GFDL and NCEP, on the other hand, use the observed three-dimensional temperatures (including the TAO data, see *McPhaden et al.* [this issue]) to initialize their forecasts. Since ENSO is a fundamental oscillatory mode of the coupled ocean-atmosphere system, one might expect such a situation, since the cyclic nature of ENSO reflects itself in many quantities in ocean and atmosphere. It is, however, unclear at present which observations are most useful in initializing ENSO predictions, and the choice seems to be model dependent, which is unsatisfactory and demonstrates that we are still at a relatively early stage in understanding ENSO and its predictability.

How do we make use of the ENSO forecasts? Present-day forecasts generally provide information about the future evolution in certain ENSO key parameters only, such as the Niño 3 sea surface temperature anomalies (SSTA) or SOI. Such information is generally not usable directly by society, which is generally interested in more detailed forecasts, say about surface temperature and rainfall or the statistics of extreme events, such as the number of frost days. Furthermore, farmers, for instance, need sometimes relatively small scale information. We have therefore to develop a suitable strategy by which the needs of society can be matched. Something can be certainly learned from the greenhouse community that faces similar problems. Regionalization strategies (statistical and dynamical) were developed, and many examples of climate impact studies are available in the literature that may be relevant also for the ENSO problem. Furthermore, uncertainties need to be assigned to the forecasts. This is only possible when suitable ensemble strategies are developed. Ensembles of forecasts can be generated by varying the initial conditions using one model only (as done with, e.g., the Lamont models) or by combining the forecast results of different prediction models into a "super ensemble," as proposed by *Fraedrich and Smith* [1989].

Finally, ENSO predictability must be discussed also in view of anthropogenic climate change. Although a discussion of the ENSO response to greenhouse warming is beyond the scope of this paper, the possibility exists that the ENSO statistics might change because of human activity. Several studies have investigated the ENSO response to greenhouse warming in coupled model experiments; the results are model dependent and widely divergent. Some models indicate no change in the ENSO statistics. Other models suggest that ENSO might become stronger and more regular. Still other models indicate that ENSO will disappear completely and that the tropical Pacific will be stuck in a warm phase. All the different scenarios will probably have very different impacts on ENSO predictability. It is therefore important to develop global coupled ocean-atmosphere models that can be used for both the investigation of anthropogenic climate change and ENSO.

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D. Anderson, Department of Atmospheric Physics, Clarendon Laboratory, Parks Road, Oxford OX20 1JE, England, U.K.

T. Barnett, Climate Research Division, Scripps Institution of Oceanography, La Jolla, CA 92093-0224.

M. Cane, Lamont-Doherty Earth Observatory, Columbia University, Palisades, NY 10960-8000.

R. Kleeman, Bureau of Meteorology Research Centre, G. P. O. Box 1289K, Melbourne, Victoria 3001, Australia.

M. Latif, Max-Planck-Institut für Meteorologie, Bundesstrasse 55, D-20146 Hamburg, Germany. (e-mail: latif@dkrz.de)

A. Leetmaa, Coupled Model Project, National Meteorological Center, 5200 Auth Road, Camp Springs, MD 20746.

J. O'Brien, Center for Ocean-Atmosphere Prediction Studies, Florida State University, Room 020, Love Building, Tallahassee, FL 32306-3041.

A. Rosati, Geophysical Fluid Dynamics Laboratory, NOAA, Princeton University, P. O. Box 308, Princeton, NJ 08542.

E. Schneider, Center for Ocean-Land-Atmosphere Studies, 4041 Powder Mill Road, Suite 302, Calverton, MD 20705-3106.

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