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El Niño prediction and predictability

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Abstract

El Niño-Southern Oscillation (ENSO) is by far the most energetic, and at present also the most predictable, short-term fluctuation in the Earth's climate system, though the limits of its predictability are still a subject of considerable debate. As a result of over two-decades of intensive observational, theoretical and modeling efforts, ENSO's basic dynamics is now well understood and its prediction has become a routine practice at application centers all over the world. The predictability of ENSO largely stems from the ocean–atmosphere interaction in the tropical Pacific and the low-dimensional nature of this coupled system. Present ENSO forecast models, in spite of their vast differences in complexity, exhibit comparable predictive skills, which seem to have hit a plateau at moderate level. However, mounting evidence suggests that there is still room for improvement. In particular, better model initialization and data assimilation, better simulation of surface heat and freshwater fluxes, and better representation of the relevant processes outside of the tropical Pacific, could all lead to improved ENSO forecasts.

Keywords: El Niño-Southern Oscillation; Prediction; Predictability

1. Introduction

El Niño, the anomalous warming of the eastern equatorial Pacific that occurs around Christmas time every few years, was first named by Peruvian fishermen centuries ago, and has caught scientists' attention in the last few decades because of its large global influence. Following the very strong, very well observed and very heavily reported event in 1997–98, El Niño became a household word, and people started to blame it for anything unusual that happened anywhere in the world. It is implicated in catastrophic flooding in coastal Peru and Ecuador, drought in the Altiplano of Peru and Bolivia, the Nordeste region of Brasil, Indonesia, New Guinea and Australia. Resulting huge forest fires on Kalimantan spread a thick cloud of smoke over Southeast Asia and crippled air travel by shutting down airports in Singapore, Malaysia and Indonesia [1]. The 1997–98 El Niño also triggered an explosion in research interest [2].

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Although the public perception of El Niño's influence is somewhat inflated, the climate impacts listed above have been shown to be strongly correlated with El Niño events at least in the past century, the period for which instrumental observations are available. There is also plenty of evidence from proxy data that El Niño has been a prominent feature of Earth's climate for at least the past 130,000 years [3,4]. The impact of El Niño is shown by the very fact that many of these proxy data, such as tree rings and oxygen isotope in fossil corals, actually reflect variations in rainfall rather than temperature. The paleoclimate record also indicates that El Niño behavior is quite sensitive to climatological conditions, so it is possible that El Niño would behave differently in our greenhouse future. Unfortunately, the long-range projections given by present climate models are far from conclusive [5,6]. We are much better off making seasonal forecasts of El Niño.

Our understanding of El Niño's dynamics started from the recognition that it is part of a coupled instability of the tropical Pacific ocean–atmosphere system [7]. Its atmospheric counterpart, the Southern Oscillation, is a seesawing of atmospheric mass, and hence of sea level pressure, between the eastern and western Pacific. The El Niño-Southern Oscillation (ENSO) cycle consists of two basic elements. First, there is a positive feedback between the zonal winds resulting from the pressure gradient, and the equatorial sea surface temperature (SST) gradient which is itself controlled by wind-driven upwelling and thermocline fluctuation; second, the equatorial ocean dynamics, particularly the non-dispersive equatorial Kelvin and Rossby waves, provide the out-of-phase element that makes the system to oscillate between warm and cold phases, namely El Niño and La Niña states [8–11]. This dynamical coupling is the essence of many ENSO models.

ENSO influences climate worldwide because it brings about large changes in the heating of the tropical atmosphere that alter the global atmospheric circulation. Since societies and ecosystems are profoundly affected, predicting ENSO one or more seasons in advance is of great importance for our wellbeing and sustainability. In fact, ENSO prediction was a major motivation and a focal point of several large international programs in the last two decades, such as the 10-year (1985–95) Tropical Ocean-Global Atmosphere (TOGA) program and the subsequent Climate Variability and Predictability (CLIVAR) program. Consequently, tremendous progress has been made in the theory, observation and prediction of ENSO [12–14]. In this paper, we briefly review the present status of ENSO prediction, discuss different opinions on ENSO's predictability, and, more importantly, suggest some potential areas for improvement of predictive skill. Our intention here is to stimulate further research on ENSO prediction and predictability rather than to provide a comprehensive review.

2. Prediction of ENSO

Experimental seasonal forecasts of ENSO started in the mid-1980s with a dynamical ocean–atmosphere coupled model [8,15,16]. This model, known to the community as the Zebiak-Cane model and later the LDEO model, is of intermediate complexity, with the aforementioned two basic elements of ENSO explicitly built into its design. Against all odds, the model for the first time demonstrated the possibility of ENSO prediction by forecasting the 1986/87 El Niño in real time. Other attempts in the same period include a couple of statistical models [17,18] and a stand-alone ocean model [19], though the latter, by neglecting the feedbacks between the ocean and the atmosphere, is only good for predicting the onset of El Niño. Barnett et al. [20] discussed the performance of several models in a case study of the 1986/87 El Niño and concluded that this particular event was successfully predicted several months in advance.

Following these early successes, a whole suite of models with different degrees of complexity have been developed for ENSO prediction over the past two decades. These models can be generally divided into three categories: purely statistical models, physical ocean–statistical atmosphere hybrid models, and fully physical ocean–atmosphere coupled models. Most of the statistical approaches are linear regression models based on matrix operations that maximize the correlation or covariance of selected predictor and predictand fields [17,18,21], though nonlinear models using neural networks [22], and self-evolving Markov models [23], have also been developed for ENSO prediction. The hybrid models couple the SST field of a physical ocean model to the surface wind field that drives the model through a statistical relationship [24,25], assuming that the memory of the coupled system is entirely contained in the ocean and that the atmospheric response to SST change is instantaneous. The assumption is grossly applicable to ENSO if high-frequency, internal atmospheric variability is not considered important. The fully physical coupled models are supposed to be at the top of the hierarchy. They range from intermediate coupled models with simplified physics [16,26] to coupled general circulation models (GCM) [27,28].

Latif et al. [14] reviewed ENSO prediction studies during the TOGA era, and concluded that models from each of the above three categories have useful skills in predicting typical indices of ENSO at lead times of 6–12 months. While fully physical coupled models seem to have more potential at long lead times, their skills are comparable to that of statistical models at lead times of 6 months or less [29]. More recently, Kirtman et al. [30] reassessed the state-of-the-art in ENSO prediction using more consistent evaluation metrics and longer periods of retrospective forecasts. They again confirmed that both statistical and dynamical models produce useful forecasts for the peak phase of ENSO up to two seasons in advance, and they also found that the ensemble forecast across all prediction systems is remarkably more skillful than any individual forecast. It should be pointed out that the predictive skill is time dependent and a good overall score does not guarantee a good forecast of a particular event. For example, Barnston et al. [31] and Landsea and Knaff [32] examined the forecasts of the 1997/98 episode by a large collection of models, and found that none of them could predict the entirety of this particular El Niño.

At present, the periods of retrospective forecasting are generally too short to distinguish between the skill scores of various prediction systems [30] and to give a confident estimate of our overall ability to predict ENSO. This is mostly due to the lack of observational data for adequate model initialization, and in part also due to the inability of present models to make effective use of available data. Recently, Chen et al. [33] performed an unprecedented retrospective forecast experiment spanning the past one and a half centuries, using only reconstructed SST data for model initialization. Fig. 1 shows the observed and predicted SST anomalies averaged in the central equatorial Pacific. At a 6 month lead, the model was able to predict most of the warm and cold events occurred during this long period, especially the relatively large El Niños and La Niñas, though the model had difficulty with small events and no-shows. This kind of skill is representative of the current status of ENSO prediction. Operational forecasts by many groups throughout the world can be found in the quarterly Experimental Long Lead Forecast Bulletin [34] and the forecast website of the International

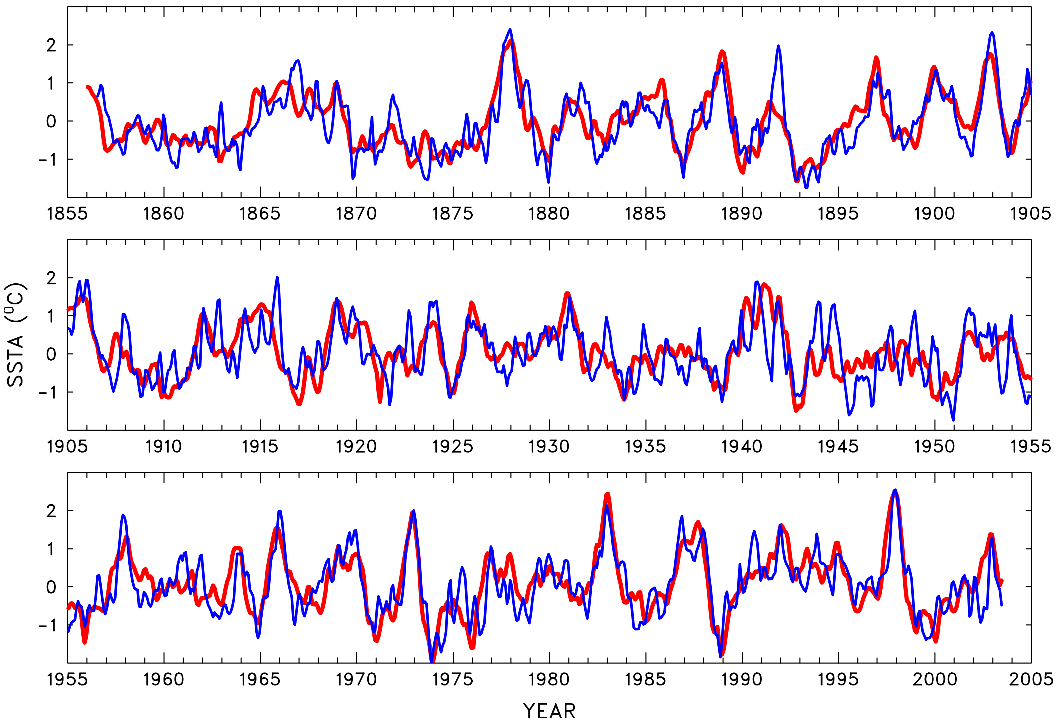


Fig. 1. Time series of SST anomalies averaged in the NINO3.4 region (5°S–5°N, 120°–170°W). The thick curve is monthly analysis of Kaplan et al., and the thin curve is LDEO5 prediction at 6-month lead. Adopted from Ref. [33].

Research Institute for Climate and Society (IRI) [35]. Despite their vast differences in complexity, present models exhibit comparable predictive skills, which seem to have hit a plateau at moderate level. Our current real-time forecasts do not appear more skillful than those made years ago [31].

3. Predictability of ENSO

There is no doubt that ENSO is predictable. The questions are how predictable it really is and how much more room there is for further improvement of our predictive skill. To answer these questions, we need to know where we stand now, what the underlying physics for predictability is, and how to measure the predictability. So far, ENSO has shown the highest predictability among all identified climate modes in the Earth's climate system, and, because of its far-reaching influences, predictions of ENSO-related tropical Pacific SST anomalies have become the basis for global seasonal forecasts of surface temperature and precipitation. For example, the two-tiered seasonal forecast system of IRI relies on the boundary conditions predicted by an ensemble of ENSO models [36,37]. It is largely due to the measurable predictability of ENSO and the quantification of ENSO's global impact that seasonal climate prediction is no longer a speculative practice.

The long-range predictability of ENSO stems from the ocean–atmosphere interaction in the tropical Pacific, the crucial role of the slowly-varying ocean in the interaction, and the low-dimensional nature of this coupled system (dominated by a few distinctive modes). Thus the key point in the debate about ENSO's predictability is the coupling strength of the tropical Pacific ocean–atmosphere system, which determines the amplitude, period and sustainability of ENSO [8]. Classic theories consider ENSO as a self-sustaining interannual fluctuation in the tropical Pacific, being chaotic yet deterministic [8–11,38]. Thus its predictability is largely limited by initial error growth, and the potential forecast lead time is likely to be on the order of years [39–41]. On the other hand, some studies emphasize the importance of atmospheric "noise" [42–44], particularly the so-called westerly wind bursts in the western equatorial Pacific [45,46], as triggers for ENSO events. In such a scenario, ENSO is a highly damped oscillation sustained by stochastic forcing, and its predictability is more limited by noise than by initial errors. This implies that El Niño events are essentially unpredictable at long lead times since their development is always accompanied by high-frequency forcing.

The difficulty of the "noise" theory is that high-frequency atmospheric noise such as the westerly wind bursts are present all the time while El Niño occurs on a distinctive timescale of 2–8 years. Thus the noise is more likely to be an "enhancer" rather than a "trigger" for ENSO. Fedorov et al. [47] tried to reconcile the different theories by considering ENSO as a slightly damped periodic oscillation modulated by random noise. In this view the dynamics of ocean–atmosphere interaction controls the timescale of ENSO, while the noise sustains the oscillation and makes it irregular. Therefore, predictability depends on both initial conditions and random disturbances, with the former determining the phase of ENSO and the latter affecting the subsequent evolution. A recent study by Chen et al. [33] shows that all of the prominent El Niños in the past one and half centuries could be predicted up to two years in advance, using a model that does not invoke any stochastic forcing. This suggests that predictability depends more on initial conditions than on atmospheric noise. Moreover, because SST is the only data used for their model initialization, and because the model is highly simplified and far from perfect, the predictive skill they obtained should be a lower bound on El Niño's predictability.

Another cause of uncertainty is in the ways we estimate ENSO's predictability. In principle, predictability can be estimated using twin-model experiments by perturbing initial conditions, but the answer is model dependent, and existing ENSO models have not been shown to be realistic enough for this purpose. Aside from one exception [33], present estimates of El Niño's predictability are mostly based on retrospective predictions over one to three decades, encompassing a relatively small number of events. With so few degrees of freedom, the statistical significance of such estimates is questionable. The uncertainty is worsened by the fact that El Niño's predictability is time dependent [48–50]. As evident in Fig. 2, the predictive skill of the LDEO model, as measured by anomaly correlations and rms errors, varies over significant range in the past one and a half centuries, especially at longer lead times. The periods with the highest overall scores, 1876–1895 and 1976–1995, are dominated by strong and regular ENSO events. The lower skill in other periods is because of there being fewer and smaller events to predict. For instance, during the 1936–1955 period, when the predictability was the lowest by all measures, there were no El Niños except for a prolonged warm event in 1940–42 (see Fig. 1).

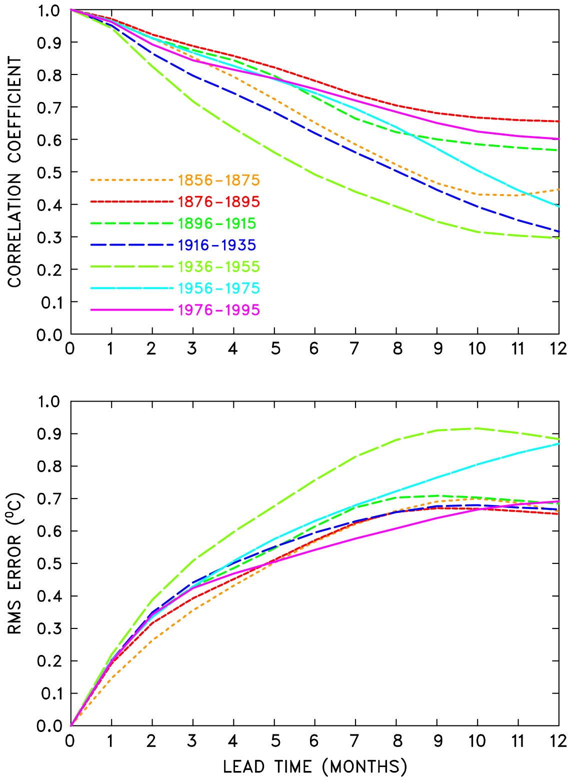


Fig. 2. Anomaly correlations and rms (root-mean-square) errors between observed and predicted NINO3.4 index. These are shown as a function of lead time, for seven consecutive 20-year periods since 1856, respectively. Adopted from Ref. [33].

In practice, due to the errors in both initial conditions and model itself, a more useful forecast strategy is to perform ensemble predictions and evaluate ENSO's predictability using probabilistic methods. As an example, Fig. 3 shows the skill of a 5-member ensemble prediction of the LDEO model measured by relative operating characteristics (ROC) [51]. Model forecasts are considered skillful when ROC curves are above the diagonal to a sufficient extent, and the farther to the upper right corner the better is the skill (the higher is the hit/false alarm ratio). It is clear that warm and cold events are equally predictable while near normal conditions are harder to predict (Fig. 3a). For instance, if four out of five ensemble members predict an event (80% probability) at 6-month lead, we expect a hit rate of 0.52 and a false alarm rate of 0.13 for both warm and cold conditions, but the corresponding rates are 0.40 and 0.17 for near normal conditions. It is interesting to note that, while at short lead times the skill decreases as the lead increases, it reaches a plateau at about 9-month lead (Fig. 3b). Forecasts made two years in advance are not much worse than those made at 9-month lead. This further indicates that skillful ENSO prediction at long lead times is indeed possible.

4. Potential areas for improvement

Generally speaking, there are four factors that limit the current skill of ENSO prediction: inherent limits to predictability, gaps in observing systems, model flaws, and suboptimal use of observational data. As discussed above, there is considerable debate on the inherent limits to predictability, but increasing evidence suggests that our current level of predictive skill is still far from those limits and surely there is room for improvement. Our task is then to improve our observing systems, models, and data assimilation methods. Tremendous efforts have been made in all these areas in the last two decades. Observation networks such as Tropical Atmosphere Ocean (TAO) array and satellite altimetry/scatterometry missions have proven invaluable for ENSO monitoring and forecasting; regional and global models with different degrees of complexity have been

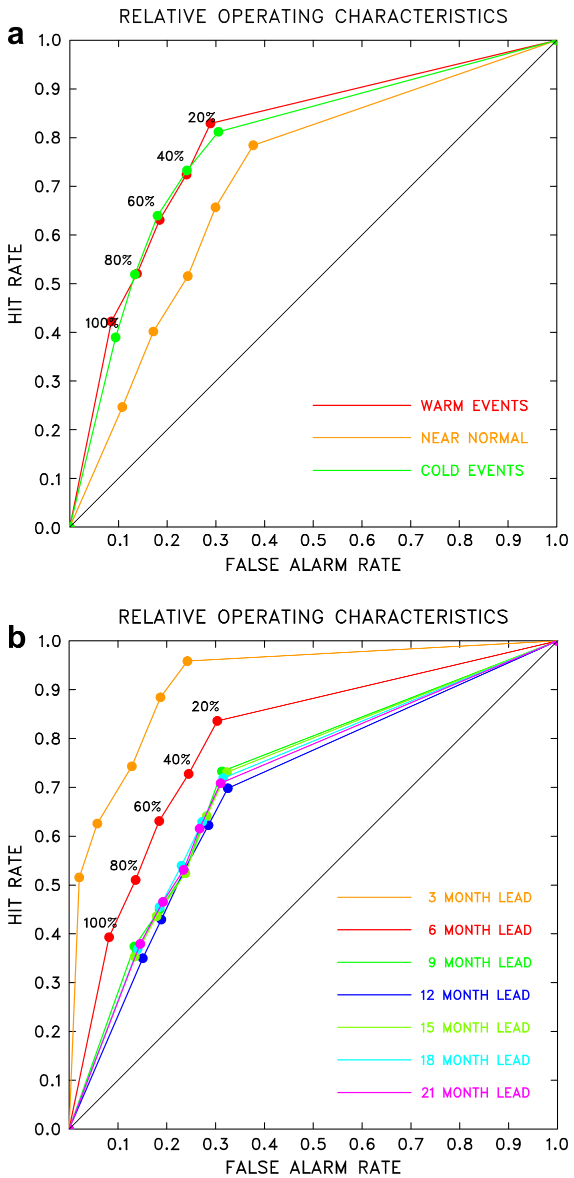


Fig. 3. LDEO model ensemble forecast skill measured by relative operating characteristics (ROC). (a) ROC curves for warm, cold and near normal conditions, respectively, at 6-month lead time; (b) ROC curves for warm conditions at various lead times. These are calculated based on 5-member retrospective ensemble forecasts for all months over the period 1856–2003.

continuously improved in terms of both physics and computational capability; and various data assimilation schemes and forecast procedures have been developed and applied to operational ENSO prediction. Here we discuss a few of the active research areas that we consider have the greatest potential for further improvement.

4.1. Coupled data assimilation and model initialization

At present, the majority of ENSO forecast models uses ocean data assimilation for model initialization. In other words, during the initialization run, observational data are assimilated into the ocean model driven by atmospheric forcing – no feedbacks to the atmosphere are allowed. This approach can produce realistic initial states, but not necessarily the optimal conditions for skillful forecasts. The reason is that, once a forecast starts, one has to rely on the coupled model which usually behaves quite differently from reality, and there may be an ‘‘initialization shock’’ at the transition from uncoupled to coupled runs. A more natural approach is to initialize model using coupled data assimilation, that is, to assimilate data, both oceanic and atmospheric, into the coupled model that is used for forecast. This should lead to more balanced initial conditions and smoother forecast start. So far there have been only a few attempts on coupled data assimilation [33,48,52,53], and most of them are based on intermediate couple models.

A NOAA-sponsored workshop on coupled data assimilation was held in the spring of 2003 to explore the possibility of implementing systematic data assimilation into coupled GCMs [54]. The workshop concluded that, for initialization of seasonal-to-interannual prediction systems, more research is needed into (1) best initialization compared with best analysis; (2) initializing coupled models; and (3) statistical correction to compensate for biases. However, coupled data assimilation presents a host of problems quite different from those in data assimilation into the forced ocean component. For example, model biases are much harder to deal with in a coupled model than in a stand-alone component model and, if they are not properly corrected, initial errors would grow fast and largely degrade forecasts. Unless we put heavy weight on models and ignore the majority of observational data (which might work for periods when models bear a strong resemblance to reality [48,55]), a prerequisite for successful coupled data assimilation is to correct systematic model biases.

Bias correction has not been given much attention in the past. The formalisms typically used in ocean and atmosphere data assimilation techniques take a ‘‘textbook’’ approach and assume that model biases do not exist. In practice, the ‘‘unbiased’’ a priori error estimates are often inflated in order to achieve consistency in a posteriori verification. Consequently, almost all successful uses of data assimilation in ENSO forecasting weight models unrealistically high compared to observations. This is particularly true for adjoint methods, which treat the model as if it had zero error. Another way of describing the same problem is to say that there is a shock when data are inserted into initial model states without taking account of model biases. The adjoint methods take the ultimate path to remove it, sacrificing the data if need be. In other schemes, the data-model difference projects onto rapidly growing error modes, resulting in a poor forecast.

The effectiveness of statistical bias correction has been demonstrated in several studies [55–57]. For example, Chen et al. [55] developed a simple interactive bias correction scheme based on the regression between model errors and model states in a reduced space of multivariate empirical orthogonal functions (MEOF). The bias-corrected LDEO model is compared with observation in Fig. 4 in terms of the leading MEOF mode. The general agreement between the two is quite striking, although some small differences remain. As compared

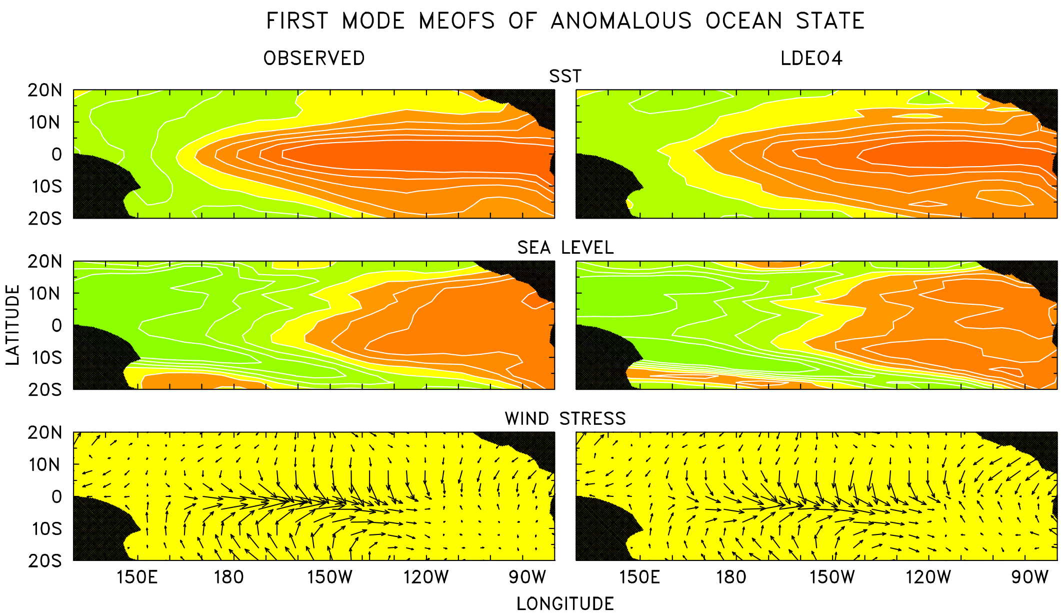


Fig. 4. First mode multivariate EOFs calculated from 24 years (1975–98) of observation (24% variance) and from 50 years of bias-corrected LDEO model run (36% variance). Adopted from Ref. [55].

to the previous versions of the model, the bias-corrected one not only exhibits a more realistic internal variability, but also performs better in ENSO forecasting (Fig. 5). More research is definitely needed along this line, especially in the analysis of the pattern, nature, and statistics of the biases, and in the implementation of proper bias correction schemes into coupled GCMs.

4.2. Surface heat and freshwater fluxes

The interannual variabilities of the surface heat and freshwater fluxes are completely ignored in intermediate coupled models and are not well simulated in coupled GCMs [58,59]. The moderate predictive skills of these models are largely built on their ability to simulate large-scale, wind-driven ocean dynamics. In other words, the coupling at work is basically dynamical: the momentum flux is the only flux from the atmosphere to the ocean that actually counts. This kind of coupling dominates in the central and eastern equatorial Pacific where SST variability is mainly controlled by ocean dynamics, but it cannot account for the ocean–atmosphere interaction in the areas where thermodynamics plays a major role. For instance, in the western tropical Pacific, SST is decoupled from the deep thermocline there and is mostly determined by surface layer thermodynamical processes. The omission or mistreatment of the surface fluxes at least partly explains why present

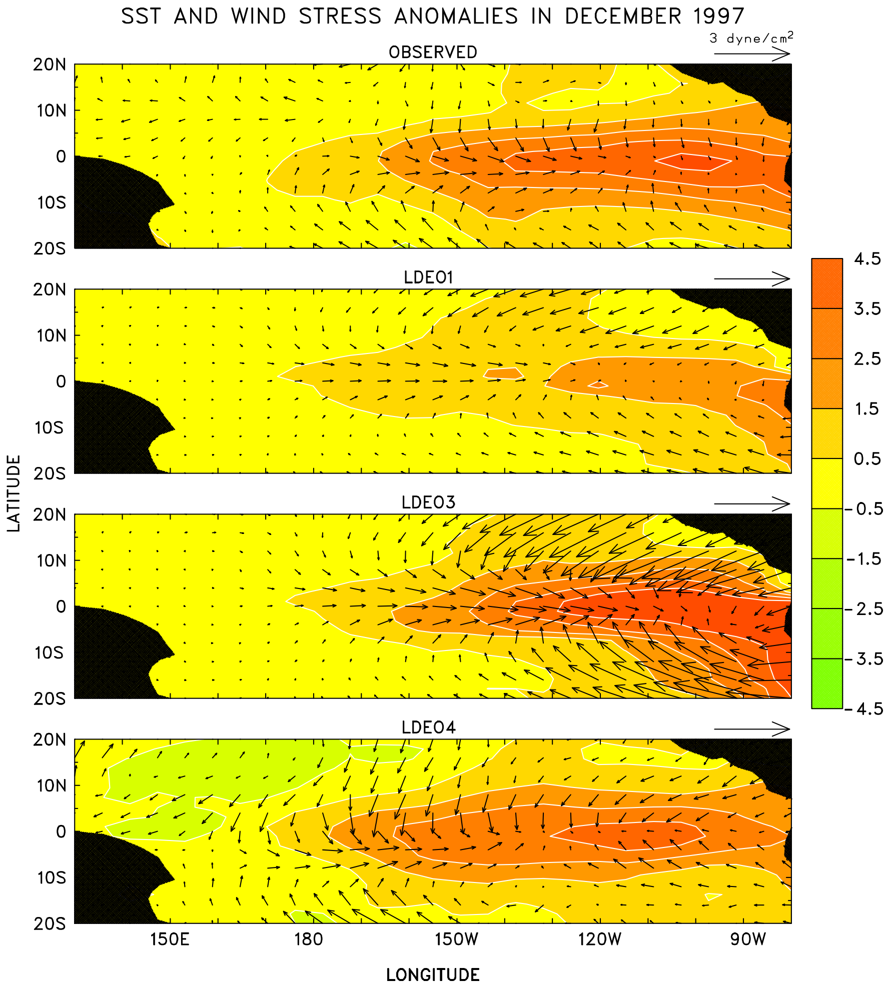


Fig. 5. Observed and forecast SST and wind stress anomalies in December 1997. Forecasts were made at 6-month lead by different versions of LDEO model. LDEO4 (bottom panel) is bias corrected while LDEO1 and LDEO3 (middle panels) are not corrected. Adopted from Ref. [55].

ENSO forecast models have little predictive skill outside of a narrow strip in the central-eastern equatorial Pacific.

Fig. 6 shows the first mode MEOFs of observed surface wind, precipitation, cloudiness and SST anomalies for boreal winter, which apparently represents the mature phase of El Niño. In association with the large SST warming in the central and eastern Pacific, there is a weaker but well defined cooling in the western and off-equatorial regions of the ocean. The cloud cover and precipitation have similar anomaly patterns, with a maximum in the central equatorial Pacific and a minimum in the western Pacific warm pool, due to the eastward migration of the warm pool and associated deep atmospheric convection. The wind field has a familiar anomaly pattern in the central Pacific: strong equatorial westerlies and associated off-equatorial convergence. There seems to be a positive local correspondence between the anomalous cloudiness and SST over most of the tropical Pacific, indicating a negative feedback from the shortwave solar radiation. Thus the effect of the cloud-forced radiation is to hamper the growth of SST, especially in the central and western equatorial Pacific. The positive correspondence between the anomalous SST and precipitation suggests a positive feedback from rainfall. The wind speed anomalies, which largely determine the anomalous evaporation, seem to have a positive feedback on SST in general. The anomalous anticyclones in the western Pacific reduce the wind speed along the coasts of East Asia and Australia, resulting in SST warming in those coastal areas. Their eastern branches, on the other hand, increase the wind speed and cool the offshore waters in the western Pacific.

The effects of anomalous fluxes of latent heat (LH), shortwave radiation (SW) and evaporation minus precipitation (E-P) have been examined in the Lamont ocean GCM. An example is shown in Fig. 7. At the surface

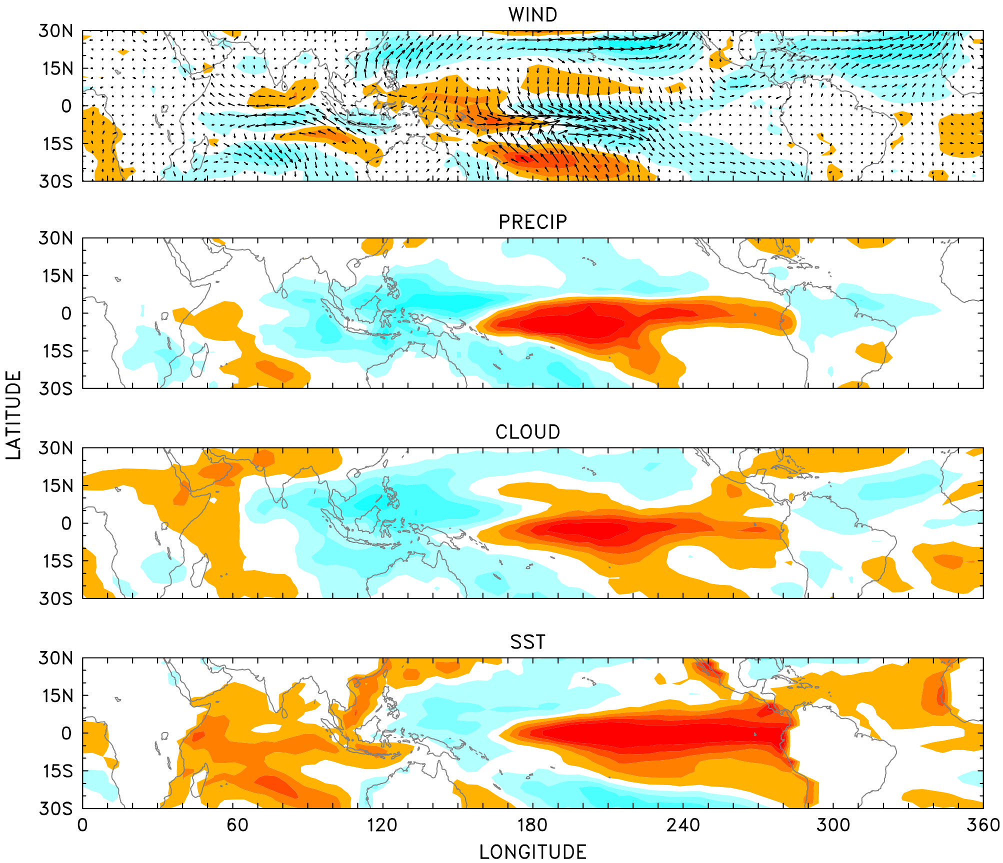
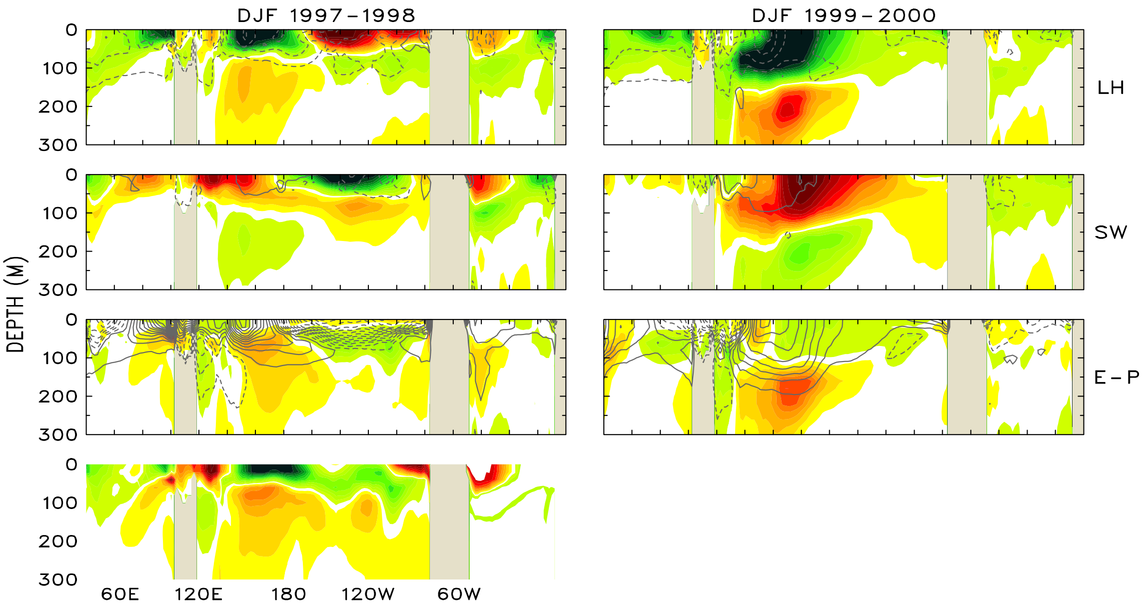


Fig. 6. First mode MEOFs (12% covariance) of December–Janauary–February wind, precipitation, cloudiness and sea surface temperature anomalies based on 16 years of observations (1984–99). Blue (red) shading is for negative (positive) values, and the sign is adjusted to be consistent with the 97/98 El Nino. Color shading in the top panel is for wind speed anomaly.



DJF 1997-1998
DJF 1999-2000
LH
SW
E-P
DEPTH (M)
0
100
200
300
60E
120E
180
120W
60W

(Fig. 7a), both LH and SW have strong impact on SST during El Niño as well as La Niña periods, with the effect of the former generally against that of the latter. However, they do not cancel out and the combined effects are still very large. Anomalous E-P has relatively small impact on SST, but it is the main contributor to the interannual surface salinity variability. These anomalous heat and freshwater fluxes also have significant effects on subsurface temperature and salinity distributions, especially in the equatorial regions (Fig. 7b). It is interesting to note that E-P has a much larger impact on subsurface temperature than on SST. In the western equatorial Pacific, the subsurface response to these anomalous fluxes is stronger and penetrates deeper during La Niña as compared to El Niño. This is because of the stronger upper ocean mixing during La Niña, when the cool water coming from the east with the enhanced South Equatorial Current overrides the warm water in the west.

The surface latent and shortwave radiation fluxes have long been suggested to have negative feedbacks to SST variations [60,61]. In such a scenario, an increase in SST would cause an increase in local evaporative cooling and a decrease in local solar heating (due to increased cloudiness). However, this kind of local relationship does not hold in general, because large-scale atmospheric circulation changes clouds and winds which in turn influence the fluxes significantly [62]. Although a negative feedback between the shortwave radiation and SST is pretty common, a positive feedback is often found between the latent heat flux and SST during ENSO events [63–65]. Rainfall has little direct influence on SST, but it affects SST indirectly by stabilizing the oceanic surface layer and changing the density structure of the upper ocean [66–68]. It has become clear that surface heat and freshwater fluxes play significant roles in the ocean–atmosphere interaction on interannual time scales; they are fundamentally important in controlling the SST variability in the western tropical Pacific; and they are quantitatively not negligible even in the central and eastern tropical Pacific. How to correctly simulate these fluxes and the associated thermodynamic coupling is a major challenge for ENSO modelers.

4.3. Influences from outside of the tropical Pacific

Although the basic mechanism of ENSO is contained in the tropical Pacific, there is mounting evidence that many epochal changes of ENSO and its predictability (see Figs. 1 and 2) are due to influences from outside, either internal or external to the ocean–atmosphere coupled system. For example, Trenberth and Hoar [69] analyzed the uniquely abnormal warming during the 1990s and attributed it to anthropogenic global warming, while Gu and Philander [70] suggested that these decadal changes are part of a natural variability of the mean thermocline in the tropical Pacific Ocean, resulting from a coupled tropical–extratropical interaction. Kirtman and Schopf [49] also considered the decadal variability as a natural one, with its amplitude amplified by uncoupled atmospheric "noise". The epochal changes of ENSO have also been related to external factors such as volcanic emissions and solar variability [71]. All of these are active research areas that may lead to improved understanding of ENSO variability and predictability.

Within the tropics, an obvious source of influence is from the Indian Ocean sector. The climate variability in the tropical Indian Ocean has been a subject of considerable debate in recent years. Many empirical analyses indicate that the dominant interannual variability in the Indian Ocean is closely related to ENSO [72–75], with a basin-wide warming during El Niño resulting from weakened Walker circulation and surface latent heat flux. On the other hand, some recent studies suggest the existence of a so-called Indian Ocean dipole (IOD), a mode of variability internal to the Indian Ocean, characterized by fluctuation of equatorial zonal temperature gradient [76,77]. It is argued, however, that a real dipole does not exist because the fluctuation is not a distinct seesaw [78,79], and that this mode is not truly independent since it is highly correlated with ENSO when the correlation is lagged and seasonally stratified. In any case, while the triggering processes of this mode of variability is not well understood, there are clear indications that, once started, it evolves through local ocean–atmosphere interaction, with dynamics similar to that of ENSO [80,81].

Because of the huge warm water pool that straddles across the western Pacific and the eastern Indian Oceans, it is only natural to assume that the climate variations in these two basins are somehow connected. The simplest picture we can derive from observations is as follows. The Walker circulation ascends above the warm pool, with easterly surface winds on the Pacific side and westerly on the Indian side, which piles waters up in the warm pool and lowers sea level and SST in the eastern Pacific and western Indian Oceans.

This produces a tripole structure with opposite zonal gradients of sea level and SST in the two oceans. When the double-cell Walker circulation weakens or strengthens, these gradients decrease or increase together, and positive feedbacks between the gradients and the Walker circulation may take place. This tripole mode is depicted in Fig. 8. The Pacific part is the familiar ENSO pattern while the Indian part is almost identical to the IOD pattern identified in Saji et al. [76]. The pattern is also evident in other analyses and coupled model runs [82,83] though it has not been explicitly described.

This mode of variability, which we refer to as Indo-Pacific Tripole (IPT), is so robust that it can be easily discerned even in raw data. Fig. 9 compares the zonal gradients of SST and sea surface height (SSH) anomalies in the equatorial Pacific and Indian Oceans, respectively. There are several points worth noting here. First of all, there is a striking out-of-phase relation between the SSH gradients in the two oceans and, to a lesser extent, between the corresponding SST gradients. This is certainly consistent with the IPT mode shown in Fig. 8, which is characterized by opposite gradients in the two oceans. Second, SST and SSH gradients in each ocean are highly correlated with each other, indicating the dynamical coupling that operates in the Pacific may also be at work in the Indian sector. Finally, it is seen in Fig. 9 that every major Pacific ENSO event over the past half a century had a counterpart in the Indian Ocean, but the opposite is not necessarily true. There were occasions, such as in the years of 1961, 1967 and 1994, when a relatively large Indian Ocean event did not seem to correspond to a similar Pacific event.

More detailed analyses reveal that IPT is an intrinsic mode of the tropical climate variability that can be excited by fluctuations in either Pacific or Indian basins, with the Pacific ENSO being the main driving force. When the mode is started from Indian basin, the Pacific side may not evolve into a full-blown ENSO episode. Instead, a weak event may occur in the western-central Pacific. This has significant implications for ENSO prediction. Under the framework of IPI, the interaction between the Pacific and Indian basins is a two-way street. Not only the Pacific ENSO has a strong impact on the Indian sector, but the Indian Ocean fluctuations can also have considerable influences on the Pacific sector, especially in those occasions when IPT is started from the Indian side. An outstanding problem in ENSO prediction is the inability to forecast weak El Niño

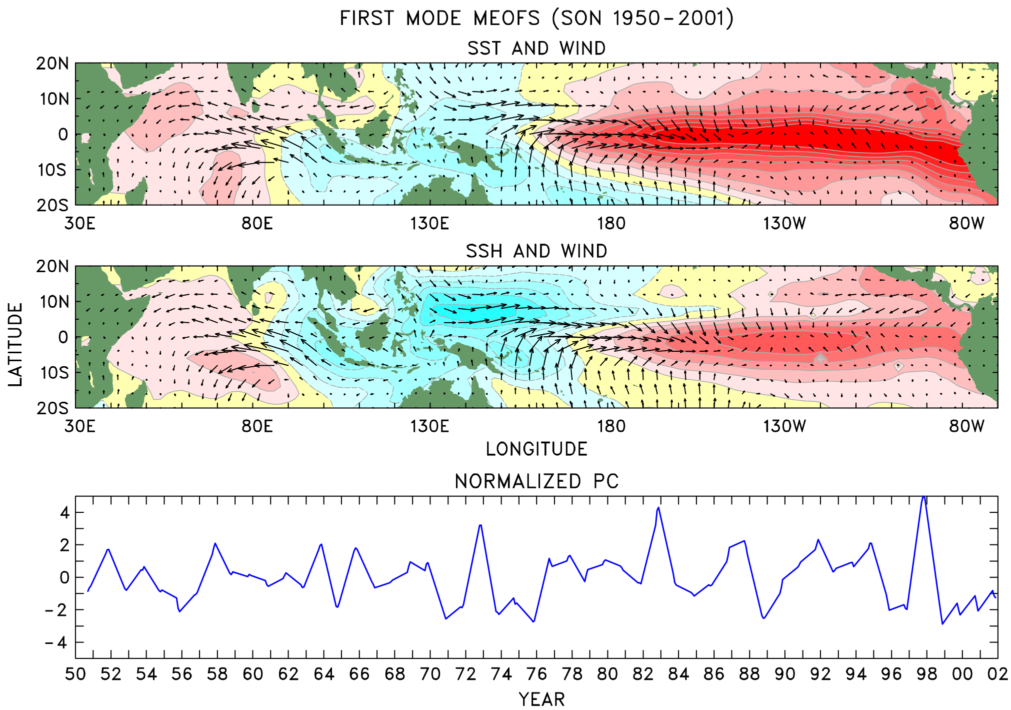


Fig. 8. Indo-Pacific Tripole as depicted by the first mode MEOFs of SST, SSH and surface wind stress calculated using SODA dataset for September–October–November (SON) over the period 1950–2001. The upper two panels are spatial patterns of SST and SSH with wind stress superimposed, and the lower panel is normalized time series (principal component) of the mode.

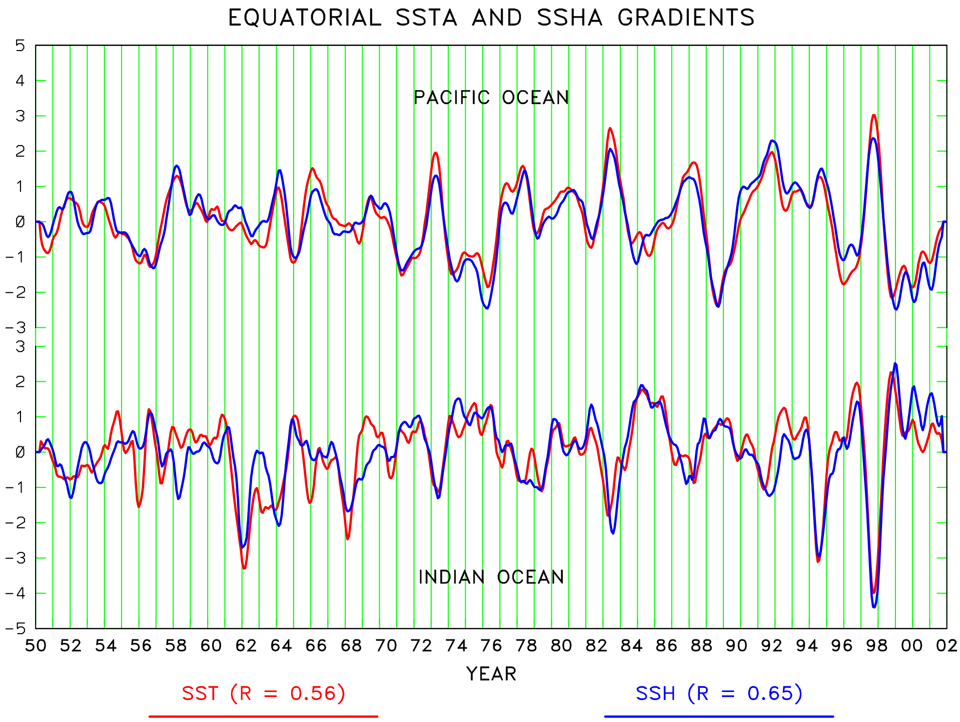


Fig. 9. Time series of zonal gradients of SST and SSH anomalies in the equatorial Pacific (upper) and Indian (lower) Oceans, calculated from the Simple Ocean Data Analysis (SODA) dataset [89]. Here a gradient is defined as the difference between the average values in two $20° \times 20°$ boxes at the eastern and western ends of each ocean. All variables are normalized by their respective standard deviations.

events which are usually centered near the dateline. At least some of these weak events are a result of IPT initiated from the Indian Ocean, and assimilating Indian Ocean data may help to solve this problem. In fact, Clarke and Van Gorder [84] improved the skill of their empirical ENSO forecast model by including the surface winds over the eastern Indian Ocean as a predictor. We need to further evaluate the impact of assimilating the Indian Ocean data, including both surface and subsurface observations, on ENSO prediction. The ongoing project of extending the TAO array into the Indian Ocean will prove invaluable for studying, monitoring and predicting tropical climate variations including ENSO.

5. Concluding remarks

We have briefly reviewed the current status of ENSO prediction and predictability studies and, in somewhat more detail, discussed several active research areas that have potential for further improvement. As a result of over two decades of intensive observational, theoretical and modeling efforts, ENSO's basic dynamics is now well understood and its prediction has become a practical venture. There is consensus among most that ENSO is predictable, but that its predictability is intrinsically limited. The remaining question is what the limitations really are. Present ENSO forecast models, in spite of their vast differences in complexity, exhibit comparable predictive skills, which seem to have hit a plateau at moderate level. However, mounting evidence suggests that there is still room for substantial improvement. In particular, better model initialization and data assimilation, better simulation of surface heat and freshwater fluxes, and better representation of the relevant processes outside of the tropical Pacific, could all lead to improved ENSO forecasts.

In some ways, it is disappointing that we, collectively, have not been able to improve ENSO forecasts more since we started this venture over two decades ago. The level of predictive skill we have achieved so far seems out of proportion to the enormous efforts and resources devoted to ENSO research and prediction. This leads to the pessimistic view that ENSO's inherent predictability is so low that our current skill is already close to its limit. However, some recent studies have shown reasons of optimism and prospects for further advances. We believe that "the fault is not in the stars (or the natural ocean–atmosphere system) but in ourselves", and that the shortcomings in our models and data assimilation schemes are the principal problem. In particular, data-model incompatibility is considered a major roadblock. To prevent initialization shock and rapid climate drift, and thus to ensure a smooth and balanced forecast start, we need to develop suitable methodologies for coupled data assimilation and to minimize systematic model biases.

We also emphasize the importance of the surface heat and freshwater fluxes, and the influences from outside of the tropical Pacific, especially that from the Indian Ocean. Supposedly, the present global coupled GCMs already have these fluxes and influences in them, and the forecasts based on these models already use global data for initialization. The questions are how well these models simulate the surface fluxes and inter-basin connections on climate timescales, and what the key parameters are for a consistent and effective initialization. The limited predictive skills of these models, and their similarity to simple models in terms of skill level and pattern, seem to suggest that they are not doing as good a job as they are supposed to do and there is still much to be done to fulfill their potential. This calls for a more detailed and systematic analysis of coupled GCM outputs, a deeper understanding of ENSO dynamics in a global context, and more efforts in process-oriented experiments using models with various degrees of complexity.

The review and discussion presented here are by no means an exhaustive account of the studies related to ENSO prediction and predictability. Some potentially important issues and research areas are of necessity left out of the scope of this paper. For example, we have not mentioned the so-called "spring barrier" in ENSO predictability, a drop of skill in persistence as well as model forecasts across the boreal spring, possibly due to the relatively small signal-to-noise ratio at this time of year [29,85,86]. It seems to be much less severe a problem in models that are properly initialized and have low level of noise [33,48]. Another interesting development we have not discussed is the recent work that considers the modulation of "noise" by ENSO itself [87,88]. It appears that high-frequency forcing such a westerly wind bursts is not purely stochastic after all – there is a deterministic part of it that strongly depends on and, at the same time, affects the low-frequency development of ENSO. Better representation or parameterization of intraseasonal atmospheric variability in coupled models may lead to improved ENSO prediction.

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