The Impact of Pacific Ocean Subsurface Data on Operational Prediction of Tropical Pacific SST at the NCEP

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ABSTRACT

The value of assimilated subsurface oceanic data to statistical predictions of interannual variability of sea surface temperature (SST) at the National Centers for Environmental Prediction (NCEP) is shown. Subsurface temperature data for the tropical Pacific Ocean come from assimilated ocean analysis from July 1982 to June 1993 and from a numerical model forced by observed surface wind stress from 1961 to June 1982. The value of subsurface oceanic data on the operational NCEP canonical correlation analysis (CCA) forecasts of interannual SST variability is assessed. The CCA is first run using only sea level pressure and SST as predictors, and then the subsurface data are added. It is found that use of the subsurface data improves the forecast for lead times of six months or longer, with some seasonal dependence in the improvements. Forecasts of less than six months are not helped by the subsurface data. Greatest improvements occur for forecasts of boreal winter to spring conditions, with lesser improvements for the rest of the year.

1. Introduction

Recently, Barnston et al. (1994) described the current status of five El Niño–Southern Oscillation (ENSO) prediction models, including models used in operations at the National Centers for Environmental Prediction (NCEP; formerly the National Meteorological Center). They reviewed and compared the current performance of the five models in their ability to make long-lead forecasts of the tropical Pacific sea surface temperature (SST) at various lead times. These models included two dynamical forecast models (the Lamont-Doherty Earth Observatory and NCEP coupled models), the hybrid coupled model of Scripps/Max Plank Institutes, and two empirical forecast models used at the NCEP, which are based on constructed analogs and canonical correlation analysis (CCA). The NCEP constructed analog model (van den Dool 1994) creates linear combinations of analogs to forecast, while the NCEP CCA (Barnston and Ropelewski 1992) uses linear relationships between fields of predictors and predictands to make forecast. All of these models have similar skill in forecasting ENSO. To date, subsurface data have not been used in the operational NCEP CCA. However, subsurface analyses of the tropical Pacific Ocean (Ji et al. 1995) make it possible to include these potentially important predictors in statistical models such as CCA.

The CCA is a multivariate linear regression technique that statistically relates field predictors to field predictands as patterns in both time and space. It has been used to produce real-time forecasts of the ENSO state at the Climate Prediction Center (formerly the Climate Analysis Center) since 1990. At the heart of the CCA, eigenanalysis is used to define the structure of the covariance between predictor and predictand sets with the constraint of maximization of cross-dataset correlation explained with each successive mode. Thus, each coefficient in the correlation matrix used as input for the CCA eigenanalysis is a correlation of a predictor and a predictand variable and is never between two predictand or two predictor variables as in ordinary or joint empirical orthogonal function analysis. More complete information on the CCA methodology is available in Hotelling (1936) and Glahn (1963), and on its application to modern climatological problems in Barnett and Preisendorfer (1987), Graham et al. (1987a,b), Barnston and Ropelewski (1992), and Barnston (1994).

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The purpose of this paper is to compare and evaluate the performance of the NCEP CCA model with and without subsurface oceanic information. In this study we make use of 11 years of assimilated ocean data from the NCEP ocean data-assimilation system (ODAS) to assess the impact of ocean data on the ENSO prediction skill scores in the NCEP CCA model. We run the CCA with and without the Pacific Ocean depth of the 20°C isotherm anomalies and dynamic height anomalies as predictors to test the importance of the subsurface information.

Section 2 describes the oceanic assimilated and model data employed, and section 3 describes the resulting prediction skill scores using the CCA. Section 4 concludes with a summary of major findings.

2. Ocean subsurface information: Analysis and model output

In the current operational version of the NCEP forecast model (Barnston and Ropelewski 1992), the predictor fields consist of global sea level pressure and tropical Pacific SST itself for several periods prior to the target time. Since the ocean responds slowly to surface wind conditions, it has been recognized for a long time (Wyrtki 1975, 1985) that subsurface ocean conditions hold a key to future variations in SST changes and associated global atmospheric circulation changes, that is, the future phase of the ENSO. Latif and Graham (1992) clearly show that the use of oceanic subsurface temperatures improves the forecast skill of tropical Pacific SSTs using a CCA model. They used subsurface temperature variations obtained from a continuous integration (simulation) of an ocean general circulation model (OGCM) for the Pacific forced by observed winds for the period from 1961 to 1985. Our approach is similar, except that instead of using simulated data we use subsurface temperatures from an assimilated Pacific Ocean analyses for the period from July 1982 to June 1993.

Great progress has recently been made at the NCEP in the actual assimilation of ocean data using OGCMs in a manner similar to how atmospheric data are routinely assimilated for use in numerical weather prediction. This ocean analysis, described by Ji et al. (1995), incorporates observed surface and subsurface temperatures into an OGCM to give a comprehensive analysis of the tropical Pacific. Since the assimilated ocean data are available for only 11 years, we use simulated ocean data for the 1961 to June 1982 period.

Monthly mean Pacific Ocean analyses for the period from July 1982 to June 1993 are used to analyze the anomalous interannual variability of the tropical Pacific Ocean thermocline depth and its correlations with subsequent SST anomalies in the eastern equatorial Pacific. The ocean reanalysis uses all available surface and subsurface oceanic observations and assimilates them into a wind-driven OGCM using an optimal interpolation objective analysis method (Derber and Rosati 1989). The July 1982–June 1993 dataset gives good quality estimates of subsurface Pacific Ocean thermal variations for the 11-yr analysis period, as shown by Ji et al. (1995). Using this ocean dataset, Smith and Chelliah (1994, 1995) examined the mean annual cycle in the tropical Pacific Ocean.

For development of the CCA, the 11-yr reanalysis gives a short data record, especially when cross validation is required. Since CCA makes predictions based on linear relationships in its training period, that period should span the widest possible range of different relationships. It is well known that the ENSO cycle is irregular with a period of between about 2 to 10 years with different types of ENSO. Therefore, with only 11 years of subsurface training data, the model may not be able to clearly recognize the development of some types of ENSO. In order to extend the record, we use output from an OGCM simulation forced with observed surface wind stress and a climatological heat flux but without data assimilation. This simulation spans the period of February 1961 through June 1993.

The ocean model used in the 33-yr Pacific Ocean simulation is the same model that was used to produce the 11-yr reanalysis. This model was developed at the Geophysical Fluid Dynamics Laboratory by Bryan (1969) and Cox (1984) and subsequently improved by Philander et al. (1987). Details of the OGCM configurations are found in Ji et al. (1995). The 33-yr OGCM simulation, applied between 29°S and 29°N, was forced by the climatological surface wind stress of Hellerman and Rosenstein (1983) combined with surface wind stress anomalies from The Florida State University (FSU), described by Goldenberg and O'Brien (1981). A drag coefficient of 1.3×10^{-3} was used for the FSU wind stress anomaly, and a drag coefficient of 1.25×10^{-3} was used for the Hellerman climatological stress. Utilization of anomalous wind stress forcing enables simulation of interannual variation of the ocean circulations. The net surface heat flux used in the simulation is the climatological flux of Oberhuber (1988). However, ocean simulations using the climatological heat flux alone often lead to excessive heating or cooling of SST during extended integrations (Stockdale et al. 1993). To avoid this, Newtonian cooling was used to constrain the SST from deviating too far from its climatological values. The Newtonian cooling information produces a heat flux correction (Q) dependent on the difference between the model SST and the climatological SST. It is computed as

$$Q = -\frac{dq}{dT}(T - T_c), \qquad (1)$$

where T is the model SST, and T_c is the climatological SST. The quantity dq/dT is the Newtonian cooling coefficient for which we use the climatological estimate of Oberhuber (1988). The choice of the climatological

SST in (1) as the constraint for the SST is made for simplicity. Since the oceanic circulation and subsurface thermal structure of the ocean are determined primarily by the surface wind stress, this constraint on SST is not expected to affect our simulation of subsurface anomalies substantially. A January 1994 Pacific Ocean weekly assimilated analysis was used as an ocean initial condition. The model was spun up for one year and forced with the climatological surface wind stress and the net surface heat flux before the 33-yr simulation was begun.

Comparison of the anomalous depth of the 20°C isotherm from the Pacific Ocean reanalysis and the OGCM simulation for the July 1982–June 1993 period shows fair agreement near the equator (Fig. 1a). The anomalies are with respect to the July 1982–June 1993 base period for both, subtracting out the model climatology to form the model anomalies and the reanalysis climatology to form the reanalysis anomalies. Highest correlations (>0.7) are found in the east equatorial Pacific. Correlations are highest near the equator, slightly south of the equator in the western Pacific, and along the coasts in the eastern Pacific. The correlations are highest in the regions where the anomaly variance is also largest (Fig. 1b), showing that the model simulates the large-scale interannual variations over the period. The normalized error is smallest over the same regions (Fig. 1c).

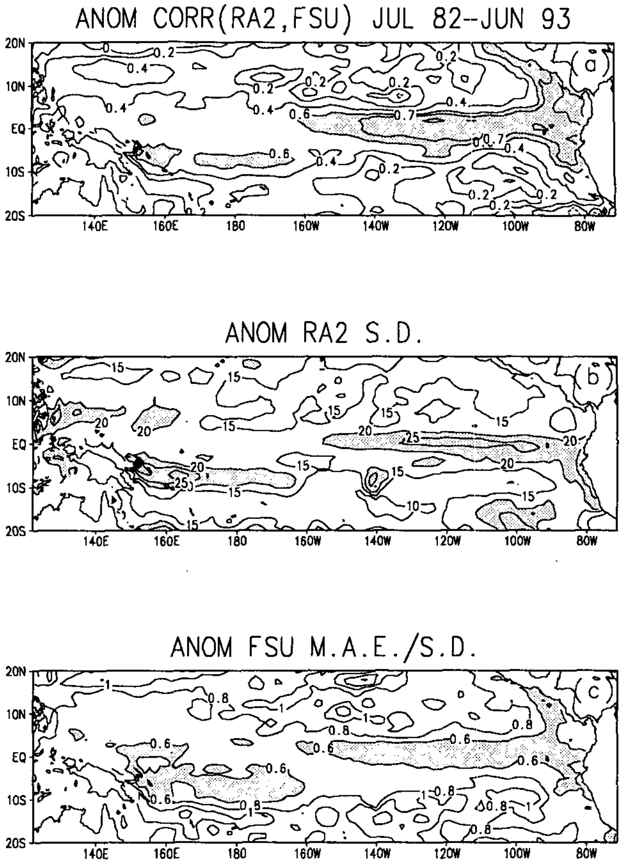

FIG. 1. Comparison of depth of the 20°C anomalies from the reanalysis and a model run for the period from July 1982 to June 1993. Shown are (a) the anomaly correlation (ANOM CORR), (b) the reanalysis anomaly standard deviation (ANOM RA2 S.D.) in meters, and (c) the simulation's anomaly mean absolute error (ANOM FSU M.A.E.) normalized by the reanalysis anomaly standard deviation.

3. CCA forecasting of interannual variability: Techniques and results

In the skill evaluations presented here, mean SST for a three-month periods are predicted using CCA in the region bounded by 5°N–5°S, 120°–170°W. This region (called Niño 3.4) yields the highest predictive skill of the eight regions tested in Barnston and Ropelewski (1992). A spatial maximum in predictive skill similarly is found near or just east of the date line by Ji et al. (1994) using their coupled ocean–atmosphere physical model. Beginning in the spring 1990, CCA-based predictions for Niño 3.4 out to four-seasons lead (i.e., five seasons later than the latest observed three-month period) appeared in the *Climate Diagnostics Bulletin* and, starting in fall 1992, in the *Experimental Long-Lead Forecast Bulletin.* Predictor fields used for the forecasts are near-global sea level pressure (SLP) and prior values of the mean SST itself in eight discrete regions covering the equatorial Pacific and eastern Indian Ocean. The SLP data are not used over some regions because of data quality problems related to mountains. The geographic extents of the SLP and SST are shown by Barnston and Ropelewski (1992). Predictors are introduced in a temporal sequence of four consecutive three-month periods ending at the time the forecast is made. Resulting predictive skills over the 1956–1990 period are reported in detail in Barnston and Ropelewski (1992).

Cross validation (Michaelsen 1987) is used to evaluate skill, where the forecast model is developed using all years except the one being forecast. There is some year to year dependency from the years on either side of the year excluded, but Barnston and Ropelewski (1992) have found its effects on cross validation skill to be slight. Each year is held out in turn as the forecast target. A correlation between the forecasts and their corresponding observations is computed to estimate predictive skill. The relative weighting of the predictor fields is determined by their approximate relative contributions to skill, which turns out to favor near-global SLP to the more local SST by about 16 to 1. While more heavily weighted SST improves the shortest lead forecasts (due to SST anomaly persistence) and helps forecasts for some seasons more than others, the weighting has been held constant over all lead times and seasons to maximize the overall skill.

Predictive skill for the 1956–1993 period is shown by the solid line in Fig. 2, using the CCA with the predictors discussed above for two- to four-season lead.

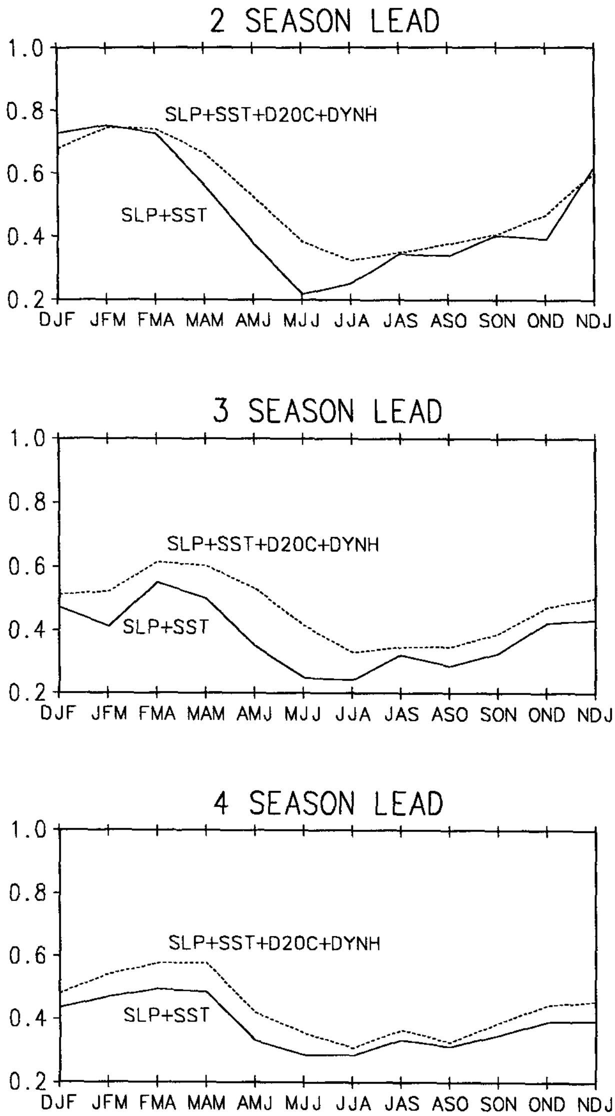

FIG. 2. The seasonal march of predictive skill in forecasting SST in Niño 3.4 (5°N–5°S, 120°–170°W) using CCA, expressed as a correlation coefficient, averaged over the 1956–1993 period. Lead times of two to four seasons [(a)–(c), respectively] are shown. The solid line indicates skill for forecasts using as predictors SLP and SST itself. The dashed line shows skill for forecasts using as predictors, in addition to SLP and SST, analyzed 20°C isotherm depth (D20C) and dynamic height anomaly predictors (DYNH) from July 1982 to June 1993 and model-reconstructed depth anomaly predictors from February 1961 to June 1982.

The lead is defined as the number of seasons skipped between the end of the final three-month predictor period and the beginning of the predicted period (i.e., no lead is a prediction period starting when the final predictor period ends). A well-defined seasonality is noted, with late winter being the best and early summer the worst predicted time of the year for the two-season lead, and early spring the best and early to mid summer the worst at the longer lead times. At two-seasons lead, the highest skill is near 0.75 and the lowest near 0.2. At three- and four-season lead the seasonal variation of skill decreases, with highest skill near 0.55 and lowest near 0.3.

To incorporate subsurface data in the CCA, we weight it according to the number of grid points in the dataset (154), which results in an effective weight of 17% as opposed to 78.6% for SLP and 4.4% for SST. Preliminary trials show that heavier weighting of the subsurface data usually does not enhance skill further. Further experimentation may lead to refinements of the present field weightings in order to optimize overall skills. Past experimentation has shown that CCA skill is not usually overly sensitive to weighting, as long as the skill-producing predictors are not strongly outweighted by ineffective predictors.

Although the anomaly depths of the 20°C isotherm cover all of the tropical Pacific, only depths between 20°N and 20°S and in areas where the reanalysis and OGCM have a correlation ⩾0.5 are used. This is done so estimates of the anomaly depths of the 20°C isotherm from the OGCM are used in regions where the OGCM skill is high (see section 2). We also use Pacific Ocean dynamic height between 20°N and 20°S in regions where the dynamic height correlation between the OGCM and the reanalysis is ⩾0.5, for the same reason. Dynamic height variations develop from changes in density over the water column. Since temperature changes in the upper ocean are primarily responsible for interannual density variations, the dynamic height variations primarily represent variations in the depth-integrated temperature over the upper ocean. They supplement the depth of the 20°C isotherm variations to give a more complete description of total ocean heat variations.

Initially, the analyzed anomaly depths of the 20°C isotherm are added for a period from July 1982 to June 1993, with zero anomaly used from 1956 to June 1982. While this did not change overall skill much for the zero- and one-season lead, for three- and four-season lead, skill is slightly increased for most seasons with greatest amounts (0.1 or more) in spring and summer. These results encouraged model reconstruction of subsurface data prior to 1982, described in section 2. Forecast skills were then computed using the model-derived subsurface temperatures from February 1961 to June 1982 and analyzed temperatures thereafter. The extended 20°C isotherm anomalies further improve skill slightly. Using dynamic height anomalies in addition to isotherm depth anomalies, with model heights used before July 1982 and ODAS heights afterward, further improves skill slightly. These skills are shown by the dashed line in Fig. 2. The greatest skill improvement comes from including the 11 years of ODAS isotherm depth anomalies. The achievement of further overall improvement justifies the use of model data for the early period.

Over the 38-yr sample, skill improvement with inclusion of subsurface temperature data is limited to spring for two-season lead but is noticeable throughout most of the year for three- and four-season leads, especially in late spring and early summer. Spring and summer, the seasons when original skill is lowest, are affected by the spring forecast barrier encountered in many ENSO prediction efforts using statistical or physical approaches. It has been recognized that prediction is most difficult when an individual event is not in progress [i.e., when the ENSO phase itself is uncertain (e.g., see Barnston and Ropelewski 1992)]. This uncertainty is greatest in spring. While knowledge of the subsurface anomaly in the central and western Pacific does not eliminate the spring barrier, it reduces it by describing approximately the amount of heat stored in the western two-thirds of the Pacific Ocean (Wyrtki 1985). Because shorter lead forecasts (e.g., zero- or one-season lead) most strongly benefit from the ability to follow an ENSO event already in progress (which is well described using SLP and SST data), those leads are helped the least by the longer-term memory provided by subsurface predictor data.

Figure 3 shows skill in similar fashion to Fig. 2 except only for the 1984–1993 period, in which analyzed subsurface predictor data are available. Comparing corresponding parts of Fig. 3 with Fig. 2, it is apparent that skill is substantially higher for 1984–1993 than for 1956–1993, both with and without subsurface predictor data. This may be because the SLP and SST data quality in the later years is superior to that of the 1950s and 1960s. Another reason might be a difference in the nature of ENSO events in the most recent decades versus that in the first half of the period. Recent events have tended to have greater amplitude, which would give the recent period greater weight in developing the statistical predictive models. Such models would be verified more favorably when applied to the portion of the period that gave rise to them, as opposed to the to the weaker and possibly qualitatively different earlier part.

The seasonality in the most recent 9 years is similar to that for skills over the full period of record. While the increase in correlation skill appears similar to that noted for the entire period, the increase in the percent variance explained is greater for the recent years because of the higher correlation to which it is added. For example, the 0.20 increase in correlation (0.35 to 0.55) for AMJ for three-season lead for the full period (Fig. 2b) represents an 18% increase in explained variance; the slightly higher correlation increase of 0.27 (0.54 to 0.81) for the recent 9 years (Fig. 3b) represents twice as large an increase in explained variance (36%).

Estimates of skill can be expressed in terms of root-mean-square error (rmse) as well as correlation. Correlation best describes the phase correspondence between forecasts and observations, which expresses forecast quality excluding correctable problems such

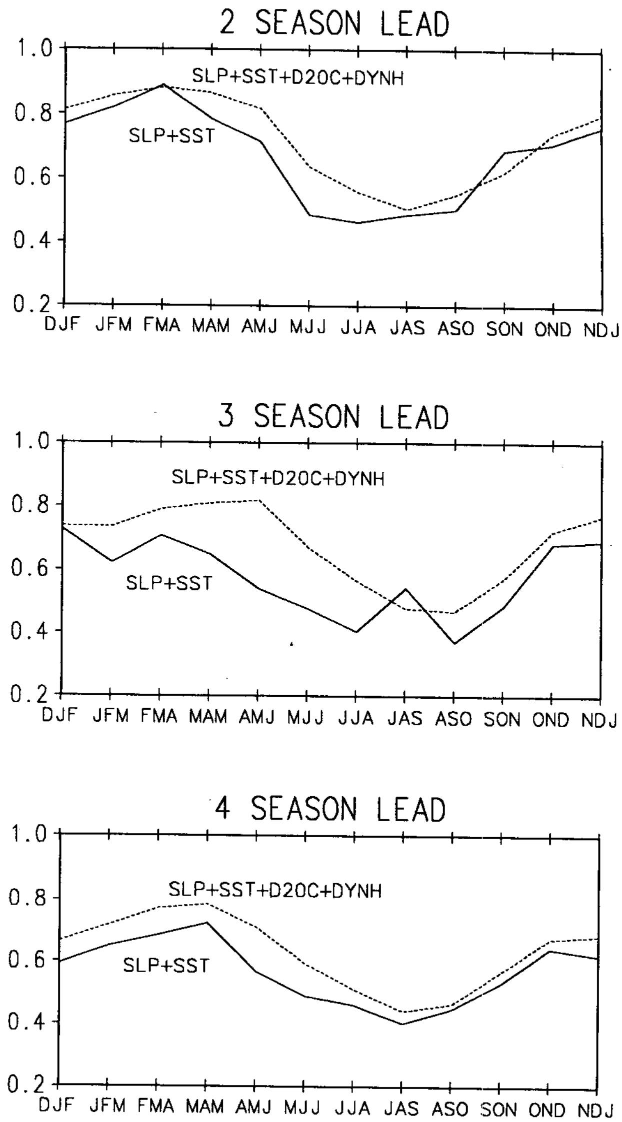

FIG. 3. As in Fig. 2 except skills are averaged over the 1984–1993 period only.

as biases and amplitude scale. The rmse measures the actual distance between forecasts and observations over all cases, which includes the negative effects of these correctable problems. When forecasts and observations are standardized, the biases and overall amplitude errors are removed. For standardized data, the average expected correspondence between correlation (r) and rmse is

$$\text{average rmse} = \sqrt{2(1 - r)}. \qquad (2)$$

For random forecasts, correlation is zero and rmse averages 1.41. When correlation is 0.5, rmse averages 1. Because the CCA forecasts and observations are standardized, the rmse skills behave approximately in accordance with (2). For example, for the above-mentioned three-season lead forecast for AMJ without subsurface temperature predictors, correlation is 0.35 and rmse is 1.16. With the use of subsurface predictors, these improve to 0.55 and 0.95, respectively.

The CCA forecast using subsurface data is currently being run parallel to the operational forecast, which does not include subsurface data. Inclusion of ocean subsurface data as a predictor slightly changes the long-lead Niño 3.4 SST anomaly forecasts. For example, following the mild to moderately warm ENSO episode that peaked in May 1993, the operational CCA forecasts for winter 1993–1994 were for continued warm conditions, while the NMC coupled model of Ji et al. (1994) called for a slightly negative SST anomaly in much of the eastern equatorial Pacific. With the subsurface anomaly predictors added, only a weak positive anomaly was predicted by CCA for Niño 3.4. The observed winter 1993–1994 SST anomaly in Niño 3.4 turned out to be less than one-half of a standard deviation above normal. Thus, the CCA forecast with the subsurface predictors verified better than the forecast that omitted them.

4. Summary of findings

Oceanic subsurface data are produced from an assimilated Pacific Ocean analysis that began July 1982 and, by necessity, from an OGCM from February 1961 to June 1982. Comparison of tropical Pacific subsurface temperatures from the OGCM with those of the ocean reanalysis for the July 1982–June 1993 overlap period shows that best comparisons are near the equator. Subsurface data are used only where the anomalies from the model and the reanalysis correlate at 0.5 or greater, which is within about 10° to 15° of the equator for both isotherm depths and dynamic height.

Subsurface data improve statistical forecasts of interannual variations of tropical Pacific SST for leads of two to four seasons. Our results are consistent with the findings of Latif and Graham (1992), who used an OGCM to develop subsurface data for CCA predictions. Improvements are larger for the boreal late winter to early summer than for the rest of the year. Correlations between observed and predicted SST increase by a maximum of about 0.20, as shown by cross validation over the entire record period. Improvement is insignificant for forecasts with zero- or one-season lead, because for those short lead times, the SLP and SST adequately describe the near-term state of the variation. Subsurface variations are an important part of the climatic system's longer-term memory and thus are more important to the longer-term state than to short-term prediction.

Improvements in forecast skill are modest but significant. One reason for the modest increase in skill may be the need to use output from an OGCM for only part of the CCA training period and to assume zero subsurface anomaly for the first few years of the training period. This was necessary because subsurface oceanic data are limited, while the CCA requires a fairly long training period to achieve stability. It is hoped that in time we may have enough higher quality oceanic data to improve forecast skill. Another reason for the modest improvement of skill is that the SLP, SST, and subsurface oceanic data are not independent. In addition, the SLP data are pieced together from two different data sources, and the earlier data are of lower quality (Barnston and Ropelewski 1992). Any errors in the SLP data degrade the CCA in general. It is hoped that the planned atmospheric reanalysis at NMC will provide higher quality and more consistent SLP and SST data for the CCA in the near future.

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