A comparison of wind products in the context of ENSO prediction

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[1] Four different wind products are evaluated in terms of their application to ENSO prediction. These wind products have been used to initialize an intermediate ocean-atmosphere coupled model for monthly retrospective forecasts from 1980 to 2002. The wind product that includes satellite scatterometer data has the highest scores, with the NCEP reanalysis and the new FSU objective analysis closely behind. The latter is a major improvement over the old FSU subjective analysis which has some serious problems in recent years. It seems that the wind products from remote sensing, in-situ observation and model reanalysis are all useful for ENSO prediction. At present, an ensemble of forecasts initialized with various wind data sets is probably our best bet. *INDEX TERMS:* 4263 Oceanography: General: Ocean prediction; 3337 Meteorology and Atmospheric Dynamics: Numerical modeling and data assimilation; 3339 Meteorology and Atmospheric Dynamics: Ocean/atmosphere interactions (0312, 4504); 3360 Meteorology and Atmospheric Dynamics: Remote sensing. **Citation:** Chen, D., A comparison of wind products in the context of ENSO prediction, *Geophys. Res. Lett.*, *30*(3), 1107, doi:10.1029/2002GL016121, 2003.

1. Introduction

[2] There is no need to elaborate on the importance of wind data for ocean modeling. Suffice it to say that a realistic simulation of the upper ocean dynamics largely depends on an accurate prescription of surface wind forcing. Although winds are internally generated in ocean-atmosphere coupled models, observational wind data are often needed for model initialization when these models are used for prediction. Most dynamical forecast models for El Niño and the Southern Oscillation (ENSO) are initialized from a wind-driven ocean state with various data assimilated [e.g., *Ji et al.*, 1994, 1998; *Kirtman et al.*, 1996]. The forecast system of Lamont-Doherty Earth Observatory (LDEO), which is the one used in this study, starts from a coupled initialization which assimilates wind as well as SST and sea level data [*Chen et al.*, 1998, 2000].

[3] There are basically three types of wind products currently used for ocean and climate studies. The first type is the traditional wind data sets based on in-situ (mostly shipboard) observations, such as those from the Florida State University (FSU) analysis and the Comprehensive Ocean-Atmosphere Data Set (COADS). The second type is the reanalysis products from data assimilated model output, such as those produced at the National Center for Environmental Prediction (NCEP) and the European Center for Medium-Range Weather Forecasts (ECMWF). More recently, a third type of wind products has emerged from satellite remote sensing, such as the wind data from SSM/I, ERS-1/2 and QuikSCAT missions. Here we compare several popular and representative wind products in the context of their application to the monthly retrospective ENSO forecasts for the past 22 years.

2. Data and Model

[4] Four wind products were chosen for this study. The FSU subjective wind analysis [*Goldenberg and O'Brien*, 1981] has been used to initialize the LDEO model ever since the model was first applied to ENSO forecasting [*Cane et al.*, 1986]. The model performed well with this wind product in the 1980s and early 1990s, but it could not work as well in recent years without the help of other data, especially in predicting the 1997/98 El Niño and the subsequent La Nina [*Chen et al.*, 1999a, *Chen*, 2001]. A new objective FSU analysis [*Bourassa et al.*, 2001] has recently become available, and it would be interesting and useful to test this new product in the context of ENSO prediction. Thus both of these FSU analyses were included in the present comparison.

[5] The other two wind products considered here are the NCEP reanalysis [*Kalnay et al.*, 1996] and a blended wind data set derived from scatterometer measurements [*Pan et al.*, 2001]. The latter is a combination of QuikSCAT, NSCAT and ERS-1/2 scatterometer winds covering the period from January 1992 to the present. For convenience, here we extended this product back to 1980 by simply using the average of the NCEP reanalysis and the FSU subjective analysis for the 1980–1991 period. A monthly climatology was calculated for each wind product and subtracted from the total wind field to obtain the anomalous wind field. The equatorial zonal wind stress anomalies of these four wind products are compared in Figure 1.

[6] Although the large-scale features of these wind products bear much resemblance, the differences among them are obvious. Generally speaking, the two FSU analyses are noisier than the NCEP and the SCAT products. There is better agreement among the data sets during warm events than during cold events. The single largest discrepancy is found in the years following the 1997/98 El Niño, when strong and persistent westerly anomalies exist in the FSU subjective analysis, but not in the other three wind products. Also noticeable is the stronger easterly wind anomalies of the FSU subjective analysis in the months preceding this large warm event.

[7] The model experiments described in the next section were carried out with the latest version of the LDEO forecast model [*Chen et al.*, 2000]. The version differs from previous ones in its inclusion of an interactive bias correction scheme. Because of the effective reduction of systematic model biases, data assimilation is more straightforward

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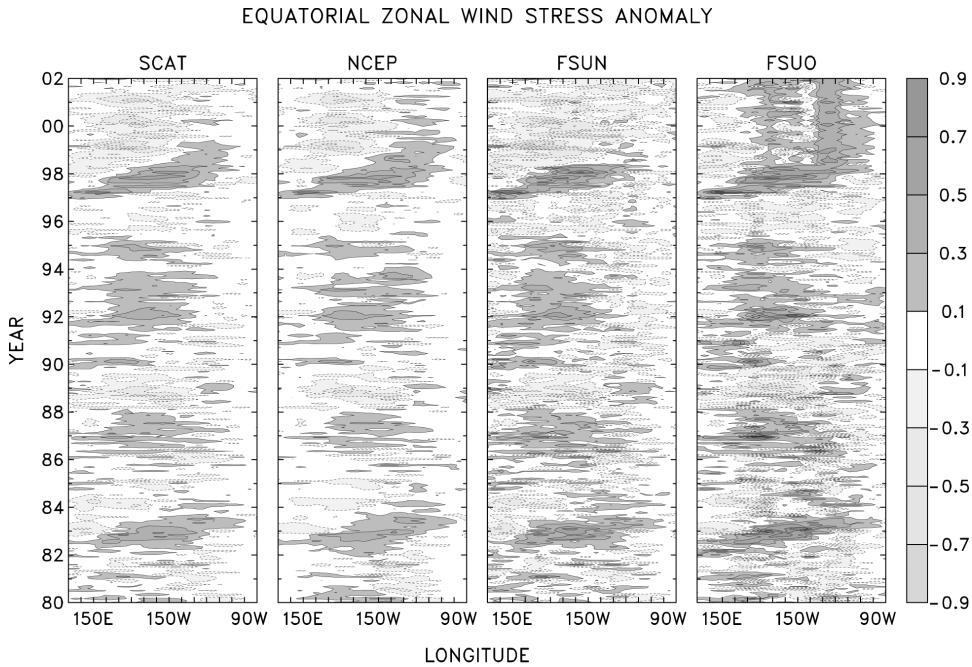

Figure 1. Zonal wind stress anomalies averaged over 5°S–5°N from the blended scatterometer wind data set (SCAT), the NCEP wind reanalysis (NCEP), the new FSU objective wind analysis (FSUN), and the old FSU subjective wind analysis (FSUO). The contour interval is 0.1 dyne/cm^2 and contour lines are dashed for values less than zero.

in the improved model. The sea level data assimilation follows a two-step approach that combines Kalman filter and nudging [*Chen et al.*, 1998], while the wind stress and SST data are simply nudged into the model. In this study, the wind data were assimilated in their full strength while the SST and sea level data were given much less weight. Thus the model experiments shown here were not designed to achieve the optimal predictive skill, but to evaluate the impact of the wind products without much influence from other assimilated data.

3. Results

[8] First, four initialization model runs were performed with the different wind data being assimilated. Figure 2 shows the model SST anomaly in the equatorial Pacific for each case along with the observations [*Reynolds and Smith*, 1994]. In all cases, the model did a good job in capturing the major ENSO events in the central and eastern equatorial Pacific. The model's lack of activity in the far western Pacific is a common problem with intermediate coupled models and is not our concern here. As expected from Figure 1, the FSU subjective wind analysis caused serious problems in recent years. It produced excessive cooling before the arrival of the 1997/98 El Niño, and a persistent warming in the eastern equatorial Pacific during the following La Nina period. These problems are eliminated in the case of the new FSU objective analysis.

[9] We next evaluate the model's forecast performance with these different initializations. Figure 3 shows the correlations between the observed SST anomalies and the 6-month lead model forecasts for the whole tropical Pacific. In all cases, the model has useful skill in a large region over the central and eastern part of the ocean and, to a much lesser extent, in the western Pacific north of the equator. The wind product that includes the scatterometer observations helps the model to achieve the best overall skill, while the NCEP reanalysis and the new FSU objective analysis are not far behind. The much lower scores of the FSU subjective wind analysis are mainly a result of its problem in the recent years. In fact, the predictive skills in the four cases are quite similar for the years before the 1997/98 El Niño (not shown).

[10] Figure 4 shows the model forecast skill for NINO3 index at lead times from 1 to 12 months. In addition to the four individual cases initialized with the different wind

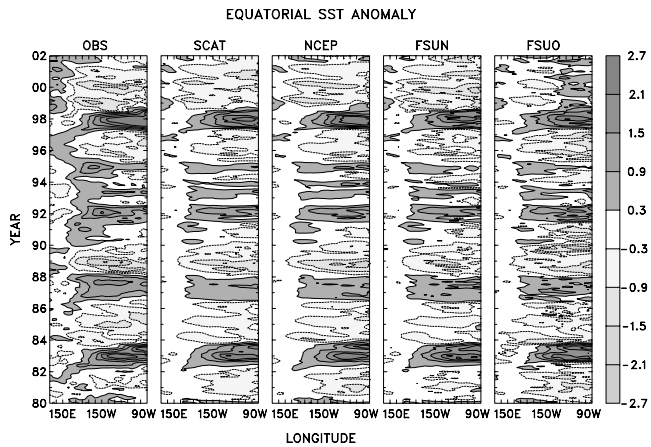

Figure 2. SST anomalies averaged over 5°S–5°N. The leftmost panel shows observational data from Reynolds analysis, and other four panels are corresponding model SST anomalies in response to different wind forcing. The contour interval is 0.6°C and contour lines are dashed for values less than zero.

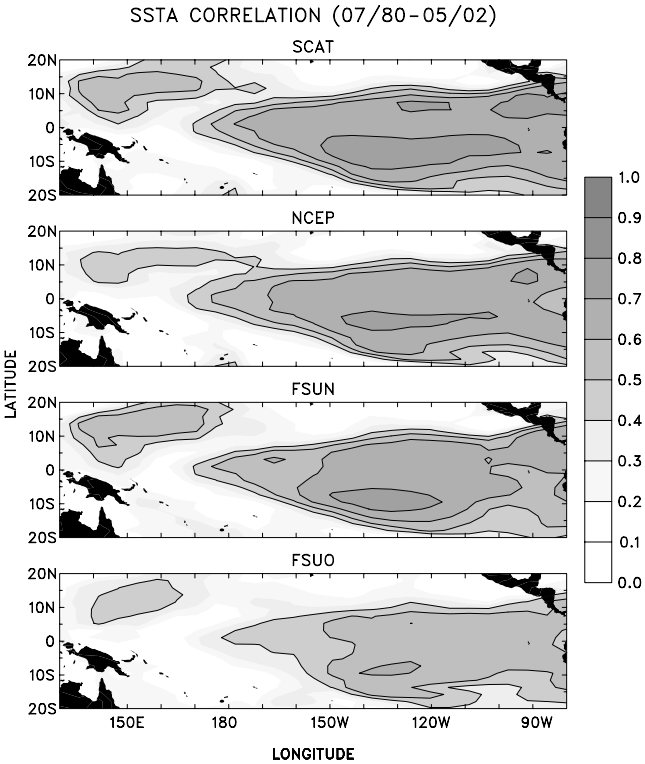

Figure 3. Correlation between observed and 6-month lead model predicted SST anomalies for all calendar months from 1981 to 2002. The contour interval is 0.1 and the areas with values larger than 0.4 are shaded.

products, an ensemble forecast averaged from the three better cases is also included for comparison. The model skill is the highest at all lead times when initialized with the scatterometer wind data, and the lowest with the FSU subjective wind analysis. The differences between these two cases are on average more than 0.1 in correlation and 0.1–0.2°C in rms error. The score with the NCEP reanalysis is almost as good as that with the scatterometer product for lead times up to 6 month, but it drops rapidly after that. In contrast, the score with the FSU objective analysis is pretty high at long leads while slightly lower at short lead times. It is interesting to note that the ensemble forecast is better than any individual one, consistent with the findings of *Kirtman et al.* [2000].

[11] Although it is a common practice to use linear correlations as those shown in Figures 3–4 to evaluate model's forecast skill, this kind of evaluation is often associated with large uncertainties. Table 1 shows the significance of the differences between various pairs of correlation curves in Figure 4 for selected lead times. This is obtained from a simple t-test after a Fisher's z transformation is applied. Each value in the table is the probability of the difference being null. Thus smaller values indicate more significant differences. It is evident that the differences between the scores of the FSU subjective analysis and those of the other three wind products are very significant at most lead times, while the differences among the scores of the three better products are only occasionally significant. In fact, our analysis revealed little systematic differences among these wind products themselves. In such a case, the ensemble average mentioned above would be the best forecast approach.

[12] Finally, as an example, Figure 5 compares the forecasts of the 1997/98 El Niño initialized with the four different wind products. The model was able to forecast this warm episode when initialized with any of these wind data sets, but the magnitude of the event was under-predicted in the cases of the FSU analyses. The scatterometer winds and the NCEP reanalysis did a better job in helping the model to predict the strength of this El Niño, though the warming

Table 1. Significance of the Differences Among the Correlation Scores of Different Cases (First Column) For Selected Lead Times (First Row)

	1	3	6	9	12
FSUO/SCAT	.00	.00	.00	.07	.29
FSUO/NCEP	.00	.00	.01	.46	.44
FSUO/FSUN	.00	.00	.11	.20	.56
SCAT/NCEP	.40	.82	.78	.29	.06
NCEP/FSUN	.79	.67	.36	.58	.18
FSUN/SCAT	.27	.52	.23	.60	.62

Smaller values indicate more significant differences.

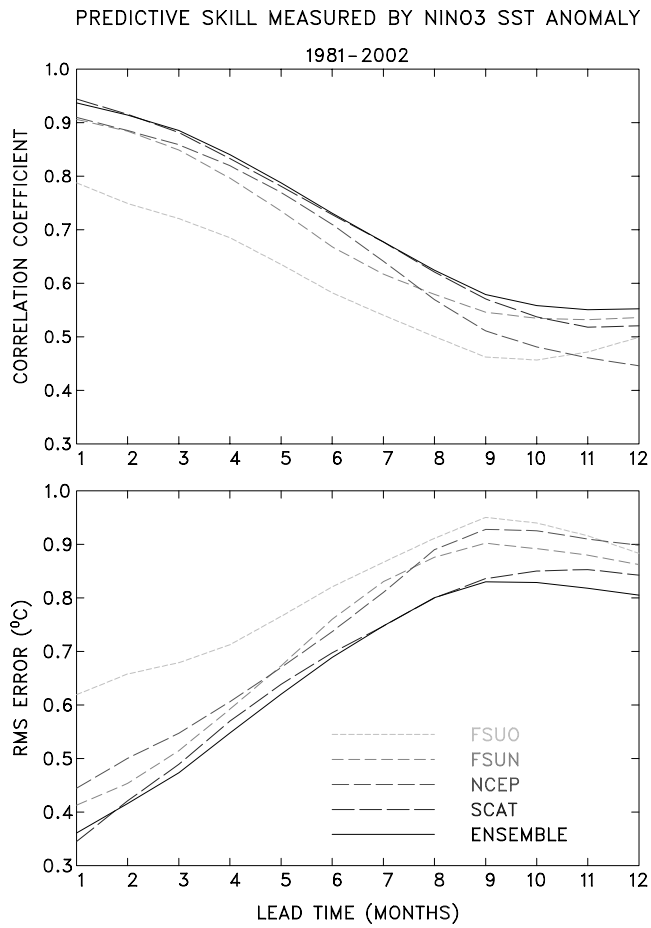

Figure 4. Correlation and root-mean-square (rms) error between observed and model predicted NINO3 SST anomalies for all calendar months from 1981 to 2002. Four dashed curves are for the individual cases initialized with FSUO, FSUN, NCEP and SCAT wind products, respectively, while the solid curve is for an ensemble of the latter three cases.

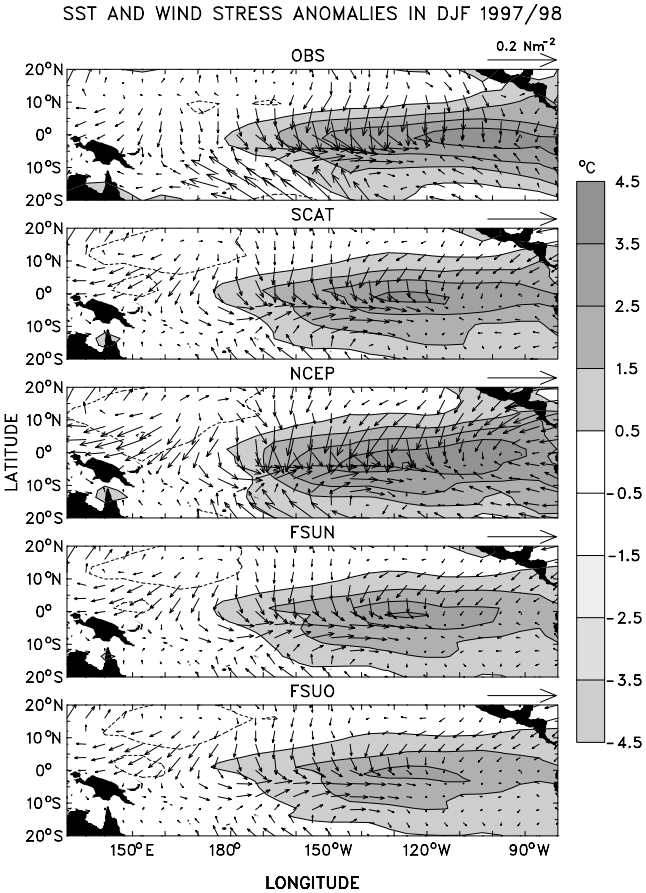

Figure 5. Observation and 6-month lead model forecasts of the SST and wind stress anomalies in the winter of 1997/98. The contour interval is 1°C and the scale for wind stress anomaly vectors is shown on top of the first panel.

center in the far eastern equatorial region was shifted westward. The LDEO model could have done better, as we have demonstrated before, if more weights had been given to the sea level and SST data during model initialization. However, as discussed earlier, we chose not to do so in this study because we did not want the effect of wind to be masked by the assimilation of other data.

4. Discussion

[13] Statistically speaking, the wind product that includes the satellite scatterometer data seems to have the best scores, but the NCEP reanalysis and the FSU objective analysis are not far behind, especially at relatively short lead times. The FSU subjective analysis does not fare well in recent years and its replacement by the objective analysis is certainly justifiable. It seems that the wind data from satellite remote sensing, in-situ observation and model reanalysis are all useful for ENSO prediction, and none of them is absolutely superior or inferior to the others, at least on the temporal and spatial scales we are considering here. Given the uncertainties in constructing each one of these wind products, the best approach is probably to run an ensemble of forecasts initialized with the various wind data available. This is exactly what we do at present for our routine forecasting.

[14] We have only evaluated the anomalous part of these wind products in this study, while in fact they do have quite different climatologies. A complete comparison should also include the effects of different climatologic wind forcing. For the LDEO model (an intermediate anomaly coupling model), this amounts to recalculating the model climatology using different wind data. We will address this issue on another occasion. It should be pointed out that the superiority of the satellite wind products in temporal and spatial coverage may not be fully appreciated by the low-resolution LDEO model. Nevertheless, as we have demonstrated in a previous study [*Chen et al.*, 1999b], higher resolution may not be a crucial requirement for climate prediction.

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References

Bourassa, M. A., S. R. Smith, and J. J. O'Brien, A new FSU wind and flux climatology, *11th Conference on Interactions of the Sea and Atmosphere*, San Diego, CA, Amer. Meteor., 912, 2001.

Cane, M. A., S. E. Zebiak, and S. C. Dolan, Experimental forecasts of El Niño, *Nature*, *321*, 827–832, 1986.

Chen, D., Applying satellite remote sensing to predicting 1999–2000 La Niña, *Remote Sensing of Environment*, *77*, 275–278, 2001.

Chen, D., M. A. Cane, S. E. Zebiak, and A. Kaplan, The impact of sea level data assimilation on the Lamont model prediction of the 1997/98 El Niño, *Geophys. Res. Lett.*, *25*, 2837–2840, 1998.

Chen, D., M. A. Cane, and S. E. Zebiak, The impact of NSCAT winds on predicting the 1997/98 El Niño: A case study with the Lamont model, *J. Geophys. Res.*, *104*, 11,321–11,327, 1999a.

Chen, D., T. Liu, S. E. Zebiak, M. A. Cane, Y. Kushnir, and D. Witter, The sensitivity of the tropical Pacific Ocean simulation to the spatial and temporal resolution of wind forcing, *J. Geophys. Res.*, *104*, 11,261–11,271, 1999b.

Chen, D., M. A. Cane, S. E. Zebiak, R. Canizares, and A. Kaplan, Bias correction of an ocean-atmosphere coupled model, *Geophys. Res. Lett.*, *27*, 2585–2588, 2000.

Goldenberg, S. B., and J. J. O'Brien, Time and space variability of the tropical Pacific wind stress, *Mon. Wea. Rev.*, *109*, 1190–1207, 1981.

Ji, M., A. Kumar, and A. Leetmaa, An experimental coupled forecast system at the National Meteorological Center: Some early results, *Tellus*, *46A,* 398–418, 1994.

Ji, M., D. W. Behringer, and A. Leetmaa, An improved coupled model for ENSO prediction and implications for ocean initialization. Part II: The coupled model, *Mon. Wea. Rev.*, *126*, 1022–1034, 1998.

Kalnay, E., et al., The NCEP/NCAR 40-year reanalysis project, *Bull. Amer. Meteorol. Soc.*, *77*, 437–471, 1996.

Kirtman, B. P., J. Shukla, B. Huang, Z. Zhu, and E. K. Schneider, Multiseasonal predictions with a coupled tropical ocean global atmosphere system, *Mon. Wea. Rev.*, *125*, 789–808, 1996.

Kirtman, B. P., J. Shukla, M. Balmaseda, N. Graham, C. Penland, Y. Xue, and S. Zebiak, Current status of ENSO forecast skill, *A Report to the Climate Variability and Predictability (CLIVAR) Numerical Experimentation Group (NEG)*, 2000.

Pan, J., X.-H. Yan, Q. Zheng, and W. T. Liu, Vector empirical orthogonal function modes of the ocean surface wind variability derived from satellite scatterometer data, *Geophys. Res. Lett.*, *28*, 3951–3954, 2001.

Reynolds, R. W., and T. M. Smith, Improved global sea surface temperature analyses using optimum interpolation, *J. Clim.*, *7*, 929–948, 1994.

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