

Incorporating a semi-stochastic model of ocean-modulated westerly wind bursts into an ENSO prediction model

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Abstract Prediction models of the El Niño-Southern Oscillation (ENSO) phenomenon often represent westerly wind bursts (WWBs), a significant player in ENSO dynamics, as stochastic forcing. A recent paper developed an observationally motivated semi-stochastic statistical model that quantifies the dependence of WWBs on large-scale sea-surface temperature. This WWB model is added here to a hybrid coupled model, thus activating a two-way SST-WWB feedback. The WWB model represents both the deterministic and stochastic elements of WWBs and thus is especially appropriate for ensemble ENSO prediction experiments. An ensemble of retrospective forecasts is performed for the years 1979–2002. Overall statistical measures of predictability are neither degraded nor improved relative to the hybrid, coupled general circulation model, perhaps because of the limitations of the hybrid coupled model and the initialization procedure used. While the present work is meant as a proof-of-concept, it is found that the addition of the WWB model does improve

the prediction of the onset and the development of the large 1997 warm event, pointing to the potential for ENSO prediction skill improvement using this approach.

1 Introduction

Westerly wind bursts (WWBs) are inextricably linked to the onset and development of every El Niño event of the last 25 years (Kerr 1999; Fasullo and Webster 2000; McPhaden 2004). To properly represent the effect of WWBs on ENSO, two processes must be taken into account. First, WWBs excite equatorially trapped Kelvin waves, which subsequently warm the eastern tropical Pacific, as seen in both observations (e.g., McPhaden and Taft 1988) and modelling studies (Lengaigne et al. 2003; Vitart et al. 2003). Second, the timing and characteristics of wind bursts appear to be modulated by the large-scale SST and by the ENSO cycle (Yu et al. 2003; Batstone and Hendon 2005; Tziperman and Yu 2007). Therefore, WWBs not only affect the ocean state but they are affected by it, and this feedback significantly affects the characteristics of ENSO (Eisenman et al. 2005; Gebbie et al. 2007). One may expect that representing this coupled feedback between sea-surface temperature and WWBs may lead to an improvement in ENSO prediction. The purpose of this paper is to present an approach for capturing this coupled feedback in an ENSO prediction model. This is meant as a proof-of-concept and we do not claim to have obtained an improved prediction skill at this point, even if we feel there is a potential for such an improvement using this approach in the future.

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Some atmospheric general circulation models forced with prescribed observed SST seem to simulate a reasonable WWB response (Vecchi et al. 2006). However, the significant biases in the climatologies of fully coupled models (Wittenberg et al. 2006) mean that the characteristics of wind bursts are also biased, even if the atmosphere-only response is good. Given these difficulties in resolving the dynamics of the WWBs, we choose to add the SST-WWB feedback as an explicit statistical model to a previously existing coupled model.

The SST-WWB feedback has been modeled in various ways and was shown to affect ENSO's characteristics, such as its amplitude, symmetry, the recurrence interval of warm events, and more (Eisenman et al. 2005; Perez et al. 2005; Gebbie et al. 2007; Jin et al. 2007). These works provided some important insight into the dynamic changes imposed by the SST-WWB feedback. To produce improved ENSO forecasts, however, the quantitative impact of WWBs must be ascertained. Gebbie and Tziperman (2008) have recently developed and tested a quantitative empirical model of the dependence of WWB characteristics on SST, which will be used here for the first time for a preliminary study of ENSO predictability. To capture the two-way nature of the feedback, the WWB model is added to a hybrid coupled general circulation model of the equatorial Pacific.

The WWB component of the new ENSO forecast model is semi-stochastic. In other words, the model is given the SST, calculates the expected WWB characteristics (amplitude, location, scale, duration, and probability of occurrence), and then produces many realizations consistent with the calculated probability of occurrence. This allows an ensemble of WWB forecasts to be made with identical initial conditions and SST, and therefore the impact of WWBs on the ENSO prediction skill may be analyzed by examining two related questions. First, is there an improvement in ENSO forecasts with the inclusion of the ensemble-mean WWB wind field? The results of the aforementioned studies suggest that the inclusion of the slowly varying ensemble mean WWB wind field should improve the prediction skill of warm events. Second, what is the loss of predictability due to the stochastic part of WWBs? The results of Roulston and Neelin (2000) and Eisenman et al. (2005) suggest that the high-frequency component of the WWBs is less important, and our simple coupled model is ideally constructed to quantify this effect. In practice, we find that the ensemble-mean WWBs do give rise to an enhanced magnitude of large warm events, but that the overall prediction skill is relatively unchanged. We emphasize that this is a preliminary proof-of-concept study using an ENSO model that lacks some important

atmospheric feedbacks, has a somewhat coarse resolution, whose parameters may not be optimally tuned by a detailed comparison to observations, and which uses a data assimilation scheme that is not state-of-the-art. Obtaining an improved ENSO prediction skill relative to current operational prediction schemes is therefore beyond the scope of this work.

We begin by describing the procedure for constructing an ENSO prediction model that includes the WWB model (Section 2). A suite of retrospective forecasts are performed for the years 1979–2002, which quantifies both the gains and losses in predictability due to the addition of the WWB model. Retrospective forecasts of the large 1997 warm event show that the added WWB model does have the potential to improve the ENSO prediction skill in the simulation model used here. We conclude in Section 4.

2 Hybrid, coupled model with WWBs

The goal of this section is to describe the procedure by which the semi-stochastic empirical WWB model of Gebbie and Tziperman (2008) can be added to an ENSO model, using as an example the hybrid coupled model based on the GFDL ocean model and a linear statistical atmosphere model (Harrison et al. 2002). We begin by discussing the observed relationship between SST and the winds.

2.1 WWB model

A westerly wind burst is defined here, necessarily somewhat arbitrarily, as any zonal wind anomaly greater than 5 m/s with a duration between 2 and 40 days and with a longitudinal extent greater than 500 km. The anomaly is defined relative to the seasonal climatology of the trade winds. The trades are easterly and as strong as 4 m/s, and thus a WWB signifies a reversal of the total wind direction. The wind stress can now be decomposed into the WWB part, τ_{wwb} , and the non-WWB part, τ_* , so that the total zonal wind stress field is $\tau_x = \tau_{wwb} + \tau_*$.

To a reasonable approximation, the zonal wind stress of a westerly wind burst can be represented by a Gaussian in space and time (e.g., Eisenman et al. 2005),

$$\tau_{wwb}(x, y, t) = A \exp\left(-\frac{(t-T_o)^2}{T^2} - \frac{(x-x_o)^2}{L_x^2} - \frac{(y-y_o)^2}{L_y^2}\right), \quad (1)$$

where x_o and y_o are the central longitude and latitude of the wind event, T_o is the time of peak wind stress, A is the peak wind stress, T is a measure of event duration, and L_x and L_y are the spatial scales. An additional WWB model parameter is P , the probability of occurrence of WWBs at a given time as calculated from the SST, which is used to determine when WWBs occur in model simulations (Gebbie and Tziperman 2008). First, the average number of WWBs per month is calculated from the observations. Then, the empirical statistical model uses this information to estimate the probability of occurrence of a WWB for a given SST distribution. In summary, the WWB model state is represented by the following vector of characteristics,

$$\mathbf{r} = [A; x_o; y_o; L_x; L_y; T; P], \quad (2)$$

corresponding to the parameters in equation (1) with P replacing T_o .

Tziperman and Yu (2007) found that although the WWB wind stress at a given location cannot be well explained as a linear function of SST, the above WWB parameters can be. Gebbie and Tziperman (2008) proceeded to present and analyze a linear regression model between SST and the WWB parameters based on this observation. They also found that it is both appropriate and efficient to represent the SST for this purpose by an expansion into SST-modes based on the left singular vectors of the SST–wind stress covariance matrix. The WWB state as represented by the above seven WWB parameters can be predicted from SST

$$\mathbf{r}(t) = \mathbf{s}_Q^*(t) \mathbf{W}_{wbb} + \bar{\mathbf{r}}(t), \quad (3)$$

where $\mathbf{r}(t)$, the WWB parameter vector at a time t , is predicted from the vector $\mathbf{s}_Q^*(t)$, which contains the amplitudes of the first Q SST modes at the time t . The WWB model is an anomaly model, and thus, the seasonal climatology of WWB characteristics, $\bar{\mathbf{r}}(t)$, is added. Here we choose $Q = 7$ based on a statistical robustness test (see Gebbie and Tziperman (2008) for details), although a smaller number of modes does not appreciably change the WWB model results. In simpler terms, the SST field at a time t is projected on the SST modes to produce the seven elements of $\mathbf{s}_Q^*(t)$, and then this vector is multiplied by the regression model matrix \mathbf{W}_{wbb} to produce the WWB parameters.

Given the model prediction of WWB parameters from the SST field, it remains to reconstruct the two-dimensional WWB wind stress field and its time evolution. The probability parameter $P(t)$ in (2) represents the likelihood that a WWB occurs at a given time. A WWB is triggered in our model whenever a random

number η , sampled at every model time step from a flat distribution between 0 and 1, is less than P . Given the time series of P , therefore, we can produce a realization of the time series of WWB occurrence times. The mean value of P is set empirically to produce an ensemble average of the number of WWBs per year that is consistent with observations. The flat random number distribution gives rise to a binomial distribution of recurrence times between WWBs, which is also similar to that observed. We emphasize that, in this WWB model formulation, the probability of occurrence is determined by the SST, but the timing of individual WWBs still contains a stochastic element. This mixture of deterministic and stochastic elements is termed “semi-stochastic” in this work.

In order to use the Gaussian form of the WWB stress in time, we need a relationship between the triggering time discussed in the previous paragraph, and the time of peak wind, T_o . Prescribing a peak time that is simultaneous with the trigger time, implies that the ocean model is forced by only the second half of the WWB life cycle. On the other hand, prescribing a peak time that is much later than the trigger time implies a long delay in the SST–WWB feedback, which is not supported by observations. Here, we choose a somewhat ad-hoc solution in which the triggering time is specified to occur a time $2.5T$ before the peak time, where T is the duration of the WWB from equation (2). With this choice, over 90% of the time-integrated wind stress is captured, and the delay between the SST and the peak WWB is no longer than 1 month.

The WWB model can be summarized as

$$\tau_{wbb}(x, y, t) = \mathcal{S}(\mathbf{r}(t)) = \mathcal{S}[\mathbf{s}_Q^*(t) \mathbf{W}_{wbb} + \bar{\mathbf{r}}(t)] \quad (4)$$

where \mathcal{S} is the semi-stochastic WWB model operator and $\mathbf{r}(t)$ can be written as a function of the SST using the WWB model. The semi-stochastic operator simply uses equation (1) with the random number process to determine if a WWB is triggered or not. The ensemble-mean component of the WWBs is defined as

$$\langle \tau_{wbb}(x, y, t) \rangle = \langle \mathcal{S}(\mathbf{r}(t)) \rangle \quad (5)$$

where the *angled brackets* represent the ensemble-mean of the WWB wind stress at a given time. Gebbie and Tziperman (2008) showed that the ensemble-mean WWB stress can be closely approximated with a deterministic operator, \mathcal{D} :

$$\begin{aligned} \langle \tau_{wbb}(x, y, t) \rangle &\approx \mathcal{D}(\mathbf{r}(t)) \\ &= \sqrt{\pi} P(t) A(t) T(t) \exp\left(-\frac{(x - X_o(t))^2}{L_x(t)^2} - \frac{(y - Y_o(t))^2}{L_y(t)^2}\right) \end{aligned} \quad (6)$$

therefore providing a shortcut to the calculation of a large ensemble.

This WWB model has been shown to capture the main WWB characteristics, including the increased likelihood of WWBs with an extended warm pool, as seen by Yu et al. (2003). A second important observed aspect of WWBs is the eastward migration of consequent WWBs with the edge of the warm pool (as opposed to the propagation of a single WWB) during the development of an ENSO event (e.g. Chang et al. 1995; Picaut et al. 1997), also well captured by this model. Given the observed SST, the statistical correlation with SST is capable of explaining the majority (59%) of the variance in the WWB parameters. The first mode, in particular, explains 46% of the variance in WWB parameters and 97% of the WWB-SST covariance.

2.2 Combining the WWB and statistical atmospheric models

The fairly standard statistical atmospheric model used here models the non-WWB wind stress as a linear function of SST by regressing the wind stress at each point on the large-scale modes of SST. By removing all WWB wind stress and developing the WWB model first, we are certain that the WWBs will not influence this part of the linear statistical atmosphere. The non-WWB wind field can then be split into a seasonally varying climatology and a residual, $\tau_* = \bar{\tau}_* + \tau_*'$. Next, the linear statistical model is derived using SVD and the linear regression method of Harrison et al. (2002). Now the non-WWB wind anomaly field, τ_*' , is decomposed into the part that can be linearly explained by the SST, τ_*^{lin} , and the part that is not linearly related to the SST, τ_*^{nl} ,

$$\tau_*^{lin}(t) = \mathbf{s}_Q^*(t) \mathbf{W}_{lin}, \quad (7)$$

and

$$\tau_*(t) = \bar{\tau}_*(t) + \mathbf{s}_Q^*(t) \mathbf{W}_{lin} + \tau_*^{nl}(t), \quad (8)$$

where $\bar{\tau}_*(t)$ is a seasonally varying climatology. The statistical atmosphere is constructed empirically from the ECMWF ERA-40 wind stress and using tropical Pacific SST (120°E–70°W and 20°N–20°S) from 1979–2002.

Deriving the WWB model with the same SST modes as the linear statistical atmosphere, we can express the total wind stress field as the following sum, corresponding to the mean non-WWB winds, the linear statistical

atmosphere, the semi-stochastic WWB model, and an unexplained residual not related to the tropical SST,

$$\tau_x = \bar{\tau}_* + \mathbf{s}_Q^*(t) \mathbf{W}_{lin} + \mathcal{S}[\mathbf{s}_Q^*(t) \mathbf{W}_{wbb} + \bar{\mathbf{r}}(t)] + \tau_*^{nl}. \quad (9)$$

In all experiments, we set τ_*^{nl} to zero, as we are only interested in the impact of the SST-modulated WWBs on prediction. This impact is analyzed by modeling the atmosphere both with and without the \mathcal{S} term in the above equation. In some cases, we are only interested in the ensemble-mean wind field, which can be computed by

$$\langle \tau_x \rangle = \bar{\tau}_* + \langle \mathcal{S}[\mathbf{s}_Q^*(t) \mathbf{W}_{wbb} + \bar{\mathbf{r}}(t)] \rangle + \mathbf{s}_Q^*(t) \mathbf{W}_{lin}, \quad (10)$$

or by using the Gebbie and Tziperman (2008) formula:

$$\langle \tau_x \rangle = \bar{\tau}_* + \mathcal{D}[\mathbf{s}_Q^*(t) \mathbf{W}_{wbb} + \bar{\mathbf{r}}(t)] + \mathbf{s}_Q^*(t) \mathbf{W}_{lin}, \quad (11)$$

which can be directly computed without any ensemble averaging. Note that the standard linear statistical atmosphere is not affected by the angled brackets, as the linear response to SST was already a deterministic model with only one possible realization.

The above decomposition of the wind stress is not unique. For example, we first decomposed the wind stress into a non-WWB and a WWB component. A different approach could be to first decompose the wind stress into components that linearly depend on the SST and a residual. With either choice, it is important to avoid double counting of the WWB wind stress and to make sure it is accounted for only in the WWB model and not in the statistical atmospheric model. This is guaranteed here because we remove the WWBs from the wind stress before calculating the statistical atmospheric model.

In proper retrospective forecasts, the empirical models \mathbf{W}_{wbb} and \mathbf{W}_{lin} should not be trained with any of the data that is to be “forecasted.” This work, however, is only meant as a preliminary examination of the incorporation of an empirical WWB model into an ENSO prediction scheme, and we have therefore not used a cross-validation procedure. We emphasize, however, that the WWB model itself has been thoroughly tested and cross validated in a previous work (Gebbie and Tziperman 2008).

2.3 Ocean model

The atmospheric model including the WWB sub-model is coupled to the Geophysical Fluid Dynamics Laboratory (GFDL) Modular Ocean Model Version 4

(MOM4 Griffies et al. 2003). The ocean model domain is global with enhanced resolution in the tropics ($1/2^\circ$ meridional resolution, 2° zonal resolution). The meridional resolution becomes coarse in the extra-tropics (4° at 50°N). The model includes an explicit free surface with freshwater surface fluxes (Griffies et al. 2001) and the KPP ocean mixing scheme (Large et al. 1994). Penetration of shortwave radiation into the surface layers is parameterized in terms of ocean color (Sweeney et al. 2005).

3 Preliminary ENSO forecast experiments

3.1 Initialization

We initialize our retrospective forecasts with a reference ocean state constructed in two steps. First, the coupled model is run with a strong Newtonian damping (5-day timescale) to observed SST and sea-surface salinity (SSS). The ocean is forced by the climatological monthly winds plus the wind anomaly calculated by the statistical atmospheric model without the WWB model. Next, the bias between the seasonal steady state and the observed SST and SSS seasonal climatologies is calculated. The model is again run to a steady state with corrected restoring surface fields to minimize this seasonal bias. Because we are using an anomaly atmospheric model, the model climatology can be fit to be very close to the SST and SSS observations. Remaining model biases include a thermocline that is slightly too shallow and too diffuse. For a full description of this procedure and the resulting model climatology, see Harrison et al. (2002) and Wittenberg (2002).

A previous paper (Gebbie et al. 2007) detailed the response of the ocean model to WWBs, using an idealized rather than observationally derived WWB model. In general, we find that the characteristics of ocean variability here are similar to the findings of the above-mentioned previous study. For instance, WWBs can be seen to generate alternating downwelling and upwelling equatorial Kelvin waves that give rise to warming in the eastern equatorial Pacific (as seen in Fig. 11 of Gebbie et al. (2007)). One model deficiency is that the SST anomalies generated by WWBs are not as strong along the South American coast as observed. For this reason, the model has better skill towards the center of the equatorial Pacific and we use the NINO 3.4 index to make evaluations. Calculations with the NINO 1,2, or 3 indices show lower model skill than in the NINO 3.4 or NINO 4 region in cases with and without the WWB model.

3.2 Retrospective forecasts

To isolate the effects of WWBs on ENSO predictability, 1-year retrospective forecasts are initialized at every January and July between 1979–2002, and run with and without the WWB model (Fig. 1). The hybrid coupled model without WWBs (green curves) generally predicts well the decay of El Niño events and the onset of La Niña events. One major model deficiency is in the prediction of the onset and growth of El Niño events (see for example the years 1982 and 1997). With the WWB model activated, an ensemble of ten runs is started with the same initial conditions as the runs without WWBs (gray curves). The ensemble mean of the WWB-enabled predictions has an enhanced amplitude for large warm episodes (red curves).

The poor skill in forecasts initialized in July can be seen in the false alarms of El Niño events in the years 1979 and 1982, for example. This failure of the prediction system is probably not due to the WWB model because the addition of WWBs did not appreciably change these forecasts (notice the similarity of the green and red lines in the bottom panel of Fig. 1). Instead, these results suggest that the underlying OGCM and the linear part of the atmospheric model may not be sufficiently realistic.

The effect of the WWB model on the predictability is analyzed by calculating the anomaly correlation and RMS prediction error as a function of prediction lead

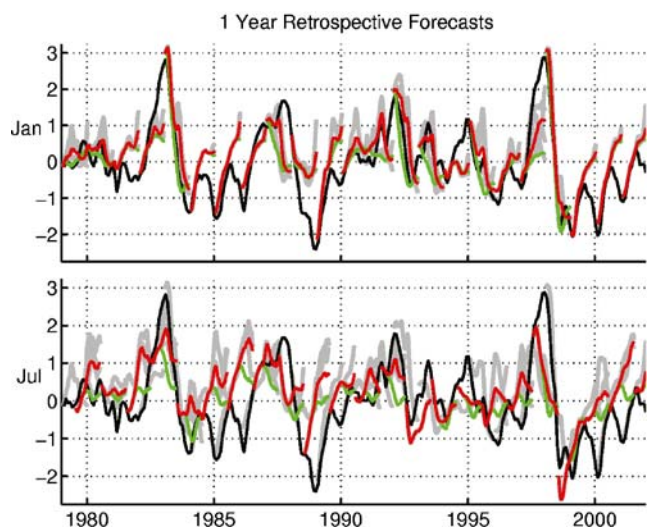


Fig. 1 NINO 3.4 index of retrospective forecasts beginning from January 1st (*top*) and July 1st (*bottom*) initialization times. The model is run without WWBs (*green*) and then with different WWB realizations (*gray curves*). The ensemble-mean of the WWB runs (*red*) can be compared to observations (*black*)

time, averaged over various groups of predictability experiments (Fig. 2). The figure shows the RMS error (panels a-d) and the correlation anomaly (e-h) of the experiments initialized in January, in July, during El Niño years and during La Niña years. We have selected the years of the largest events, i.e., 1983, 1988, and 1997, as the El Niño years, and 1989 and 1999 as the La Niña years in our analysis. These experiments show that the model does better than persistence on most measures (except July initializations, see Landsea and Knaff 2000). However, these objective statistical measures do not demonstrate a clear advantage to using the WWB model. One would have hoped that the prediction would improve during the El Niño years, and indeed the RMS error seems to be somewhat reduced during days 150-250 or so (panel c). But the anomaly correlation actually shows an opposite signal of reduced prediction skill during El Niño events (panel g).

A detailed examination of individual predictions shows that the model misfit to observations is generally negative when the NINO 3.4 index is positive, and vice versa (not shown). The implication of this finding is that the model dynamics are either overly damped or need stronger forcing or both. The stability (degree of damping) of our hybrid, coupled model depends crucially upon the upper ocean-mixing parameters and heat-flux restoring timescale. Another issue is that the

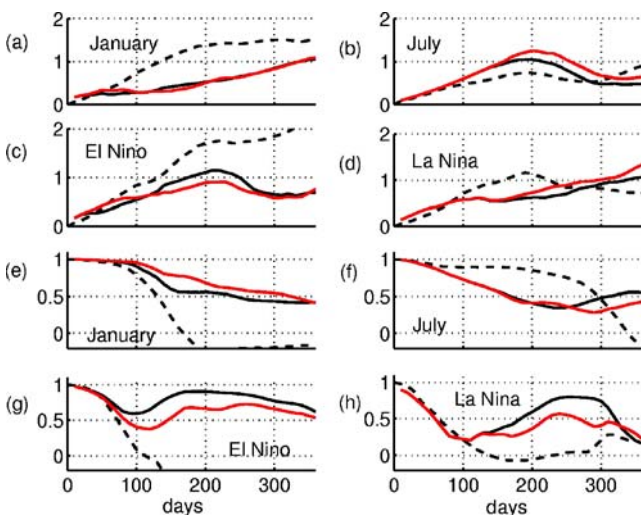


Fig. 2 Predictability of ENSO with and without the WWB model. The upper four panels show the RMS errors for a prediction of the NINO 3.4 index ($^{\circ}\text{C}$) relative to persistence (*dash*), and based on the hybrid coupled model with (*red*) and without (*black*) the WWB model. The RMS is shown averaged over **a** all January initializations, **b** all July initializations, **c** over Niño years and **d** La Niña years. The lower four panels show the anomaly correlations for the same cases

atmospheric model does not include τ_*^{nl} , a part of the wind stress, which would generally increase the overall energy level in the tropical Pacific Ocean. Further studies with this model should focus on the impacts of these issues.

Even without a statistically significant improvement in prediction skill, we will next show that the WWB model has the potential to improve the simulation of the onset of warm events. To see this, we next consider the effect of model WWBs on the 1997 event.

3.3 Focus on the 1997 El Niño

The hybrid coupled model without the WWB representation forecasts only a weak warming in the eastern tropical Pacific for the 1997 event (dash line in Fig. 3). When the semi-stochastic WWB model is included and ten ensemble members are run, the ensemble-mean NINO 3.4 index indicates a greater growth of the El Niño event on average. One member of the WWB ensemble was even able to predict the proper onset of greatest growth in March, 1997. Over the first 11 months of the forecast, the run without any WWBs was generally a lower bound on the predicted growth.

Figure 4 summarizes the relevant statistical results of the 1997 prediction experiment. The ten semi-stochastic realizations of the NINO 3.4 index are averaged and denoted ($N(WWB)$) in Fig. 4. This ensemble average shows that the predicted warming is larger than

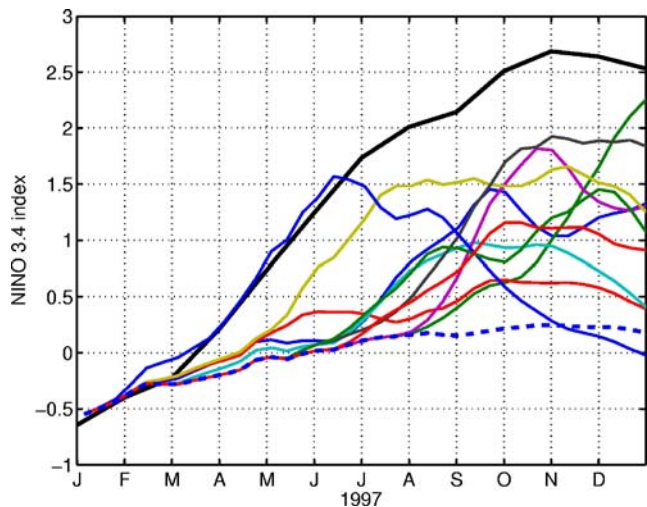


Fig. 3 The effect of the WWB model on the prediction of the 1997 event: shown is the NINO 3.4 index for observations (*thick black line*), a retrospective forecast of the hybrid coupled model without WWBs (*dash line*), and multiple forecasts from different realizations of the hybrid coupled model including the semi-stochastic WWB representation (*thin colored lines*)

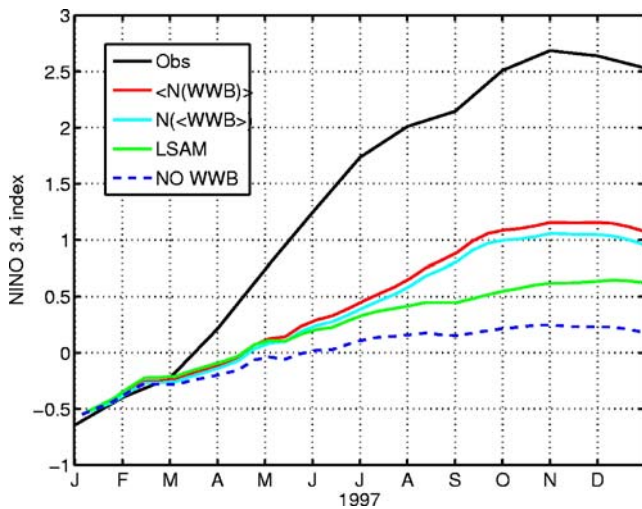


Fig. 4 A summary of the 1997 model forecast experiments. Shown is the NINO 3.4 index for 1997 in observations (*black*), a retrospective forecast without WWBs (*dash*), the ensemble average of model simulations with multiple realizations of WWBs (*red*), a forecast forced by the expected ensemble-averaged WWB activity (see text, *cyan*), and a forecast with a linear statistical atmosphere fitted to the WWBs but without the WWB model (see text, *green*)

that without the WWB model (*dash*) by about 1°C , although it still underestimates the observed warming for this event. The remaining discrepancy could be due to the overly damped nature of our model, especially the overly diffuse equatorial Pacific thermocline. Another possibility, raised in Gebbie and Tziperman (2008), is that the extreme number and amplitude of observed WWBs in 1997 can only be partially linked to the SST.

In order to test whether the detailed timing of individual WWBs is important, a forecast was forced by the deterministic ensemble-mean WWB wind forcing of equation (11). In this case, the ocean is forced with the expected value of the WWB wind stress, corresponding to the ensemble average WWB magnitude. The prediction run forced by the WWB wind stress of this amplitude is denoted $N(\langle WWB \rangle)$ in Fig. 4 (*cyan* curve). In this case, the WWB wind stress is smooth in time, and the total westerly wind stress integrated over both space and time is nearly identical to that of the semi-stochastic WWB model realizations. The resulting predicted warming is very similar to the ensemble mean, consistent with the previous results indicating that the precise timing of individual WWBs is less important than the slow component of the WWBs (Roulston and Neelin 2000; Eisenman et al. 2005; Zavala-Garay et al. 2005).

Although the timing of each WWB in our model is semi-stochastic, this result implies that ENSO predic-

tion in this model is not greatly affected by the stochastic nature of the WWBs. This may also imply a greater predictability skill than one could have hoped for if the WWBs were completely stochastic and if the ENSO prediction were sensitive to the stochastic component of the WWBs.

Finally, we test whether an explicit WWB model is necessary at all. As mentioned above, some of the wind stress signal of the WWBs is linearly correlated with the SST and may be captured by a standard linear statistical atmospheric model (LSAM). We derive such a statistical atmospheric model by using the wind data without filtering out the WWB signal (Gebbie et al. 2007), and perform a forecast experiment (marked “LSAM” in Fig. 4). The observed warming is significantly weaker than the one found with the WWB model included, indicating that the WWB model does enhance the magnitude of large warm episodes and reduce the model and prediction errors. These results indicate that while using an explicit WWB model does not seem to improve the statistical measures of ENSO predictability in the hybrid coupled model used here, it still has the potential to improve the prediction skill for large warm events.

4 Conclusions

The first objective of this work is to develop and test a practical, observationally based approach for westerly wind bursts (WWBs) in ENSO simulation and prediction models. The model used here includes the effects of SST on the WWB characteristics, as well as a representation of the stochastic element of the WWBs (Gebbie and Tziperman 2008). Our second goal is to perform some preliminary tests of the effect of this procedure on the prediction skill in an ENSO retrospective forecast framework with a simple initialization scheme.

The WWB model was included in a hybrid coupled model based on an ocean GCM and a statistical atmospheric model, and the ocean model was initialized with a simple nudging to the observed SST and SSS of the period 1979–2002. We find that statistical prediction measures such as RMS of prediction error and anomaly correlation for forecasts started in January and July show neither a significant improvement nor a degradation in ENSO forecast skill relative to the same model without a WWB component. However, the WWB model was shown to result in an enhanced warming and improved prediction skill for the major warming El Niño event of 1997.

The lack of prediction skill improvement may be due to the insufficient horizontal and vertical resolution of the model used here, the possibly sub-optimal tuning of some model parameters, or the initialization scheme used. It would be interesting to use the same procedure outlined here for including the WWB model, but with a state of the art ENSO prediction model and data assimilation scheme, including higher horizontal and vertical ocean model resolution and a more complete atmospheric model.

If the WWB model is included in an atmospheric GCM that produces some WWB-related variability, even if not realistically, one would need to be careful not to include the effect of WWBs twice. Therefore, the WWB model derivation would need to be modified such that it complements and corrects the GCMs WWB variability rather than ignoring it. Such an extension is beyond the scope of this paper.

We emphasize the preliminary, proof-of-concept nature of this study. The results presented here, especially for the 1997 event, provide an indication that the proposed approach may be fruitful in the near future. By implementing an explicit WWB model into an ENSO prediction model, we have been able to isolate the potential impact of WWBs on the predictability of the tropical Pacific coupled system. The computational efficiency of the WWB model introduced and tested here also makes it very attractive for ensemble prediction studies. The combination of an ensemble approach and the empirical WWB model can be used to directly estimate the loss of predictability due to the stochastic element of the WWBs. This empirical WWB modeling approach may be helpful for improving operational forecasts even in ENSO prediction models based on oceanic and atmospheric GCMs that do not properly simulate WWBs on their own.

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