A kind of initial errors related to "spring predictability barrier" for El Niño events in Zebiak-Cane model

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[1] Seasonal dependence of initial error growth for El Niño-Southern Oscillation (ENSO) in Zebiak-Cane model is investigated by using a new approach, i.e. conditional nonlinear optimal perturbation (CNOP). It is found that CNOP-type error tends to have a significant season-dependent evolution, and produces most considerable negative effects on the forecast results. Therefore, CNOPs are closely related to spring predictability barrier (SPB). On the other hand, some other kinds of initial errors, whose patterns are different from those of CNOPs, have also been found. Although the magnitudes of such initial errors are the same as those of CNOPs in terms of the chosen norm, they either show less prominent season-dependent evolutions, or have trivial effect on the forecast results, and consequently do not yield SPB for El Niño events. The results of this investigation suggest that the CNOP-type errors can be considered as one of candidate errors that cause the SPB. If data assimilation or (and) targeting observation approaches possess the function of filtering the CNOP-type or (and) other similar errors, it is hopeful to improve the prediction skill of ENSO. **Citation:** Mu, M., H. Xu, and W. Duan (2007), A kind of initial errors related to ''spring predictability barrier'' for El Niño events in Zebiak-Cane model, *Geophys. Res. Lett.*, *34*, L03709, doi:10.1029/2006GL027412.

1. Introduction

[2] Considerable efforts have been invested in studying the El Niño-Southern Oscillation (ENSO) phenomenon [*Philander*, 1990; *McCreary and Anderson*, 1991; *Wang and Fang*, 1996; *Jin*, 1997; *Neelin et al.*, 1998; *Wang*, 2001]. An important aspect of these studies is on the exploration of "spring predictability barrier (SPB)" for ENSO. Some possible mechanisms have been given to explain this phenomenon [*Webster and Yang*, 1992; *Moore and Kleeman*, 1996; *Lau and Yang*, 1996; *Samelson and Tziperman*, 2001]. *Chen et al.* [2004] reported that by using the initial field produced by a data assimilation approach, SPB in the model of *Zebiak and Cane* [1987] (CZ model) is not as severe as that in persistence or in most other forecast models, which indicates the importance of the accuracy of initial fields in ENSO predictability. This study motivates us to investigate SPB problem in view of the development of initial errors. Since seasonal dependence of initial error growth is related to SPB, naturally we are required to answer the following questions: what kind of initial errors induce the significant season-dependent evolution and then cause the severest prediction uncertainty of model ENSO? If a data assimilation or (and) targeting observation approaches filter such kind of initial uncertainty, can the ENSO forecast skill be improved? *Mu and Duan* [2003] utilized the approach of conditional nonlinear optimal perturbation (CNOP) and a theoretical ENSO model to study the predictability of ENSO and its related SPB. CNOP approach has also been employed by *Duan et al.* [2004] to study the optimal precursors of ENSO, and by *Mu et al.* [2004] to investigate the nonlinear instability of ocean's thermohaline circulations. All these works show that CNOP is a useful tool to deal with these problems, which suggests applying CNOP approach to investigate SPB of the CZ model in this paper.

2. Method

[3] The CZ model is a well-known one and has been used in the prediction and study of ENSO extensively. The model describes the essential physics of ENSO, and thus provides a convenient tool for investigating the SPB of ENSO.

[4] To study the prediction uncertainties of ENSO caused by initial error, we construct a cost function to measure the evolution of initial error. Then the aforementioned CNOP, which has largest effect on prediction uncertainties and is denoted by $\vec{u}_{0\delta}$, can be obtained by solving the following nonlinear optimization problem

$$J(\vec{u}_{0\delta}) = \max_{||\vec{u}_0||_1 \leq \delta} ||\vec{T}'(\tau)||_2, \quad (1)$$

where $\vec{u}_0 = (w_1\vec{T}'_0, w_2\vec{h}'_0)$ is the non-dimensional initial errors of SSTA and thermocline depth anomaly, $w_1 = (2°\mathrm{C})^{-1}$ and $w_2 = (50\ \mathrm{m})^{-1}$ are the characteristic scales of SST and thermocline depth. $||\vec{u}_0||_1 \leq \delta$ is the constraint condition defined by the prescribed positive number δ and the norm $||\vec{u}_0||_1 = \sqrt{\sum_{i,j}\left\{\left(w_1 T'_{0i,j}\right)^2 + \left(w_2 h'_{0i,j}\right)^2\right\}}$, where (i,j) represents the grid point in the region with latitude and longitude respectively from 129.375 E to 84.375 W by 5.625 and from 19 S to 19 N by 2, $T'_{0_{i,j}}$ and $h'_{0_{i,j}}$ denotes the dimensional initial errors of SSTA and thermocline depth anomaly at grid point (i,j). The evolutions of these initial errors are measured by the norm $||\vec{T}'(\tau)||_2 = \sqrt{\sum_{i,j}\left(w_1 T'_{i,j}(\tau)\right)^2}$. And $T'_{i,j}(\tau)$ is obtained by subtracting SSTA of reference states (i.e. the "true states" to be predicted) at time τ from the predicted SSTA, the latter is achieved by integrating CZ model from time 0 to τ with initial condition being initial value of reference state plus its error $\vec{u}_0$.

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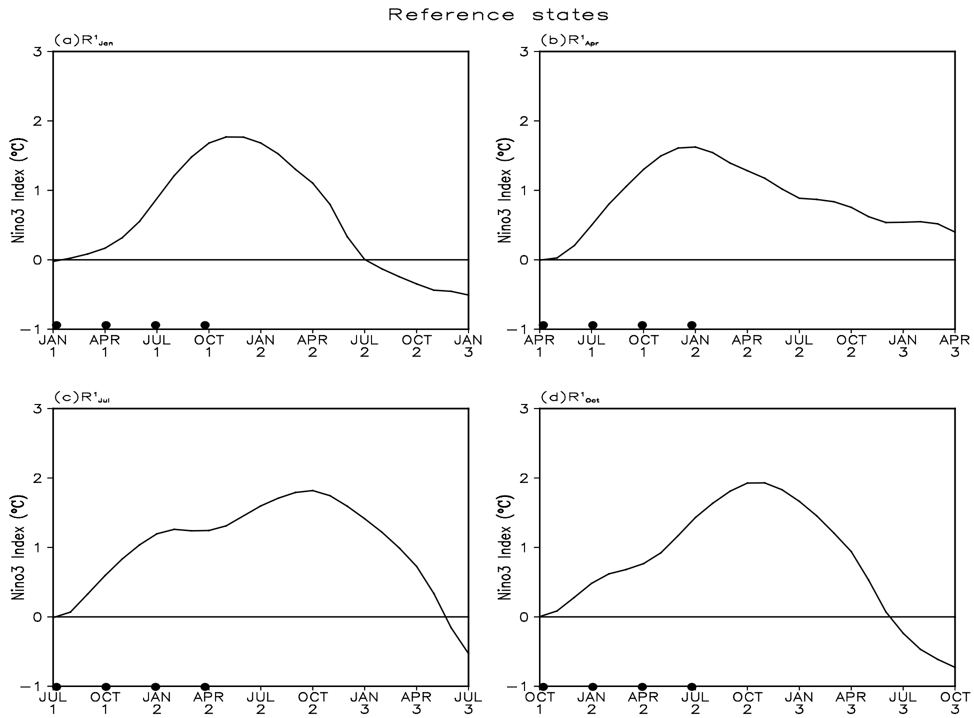

Figure 1. Niño-3 index of reference states with initial warming time being (a) January, (b) April, (c) July, and (d) October. The dots located on horizontal axis denote the initial time of prediction, i.e., the start months.

[5] To obtain CNOPs by solving nonlinear optimization equation (1) numerically, a solver of Spectral Projected Gradient 2 (SPG2) algorithm is used. Detailed description of SPG2 were given by *Birgin et al.* [2000]. In this algorithm, the gradient of cost function with respect to initial value is of importance. To calculate the gradient efficiently, we have developed the tangent linear and adjoint models of CZ model. The correctness of them are verified, which guarantees that correct gradients can be provided by the adjoint model.

3. Results

[6] A large number of reference states, which are generated by integrating CZ model with proper initial values, are chosen to address the season-dependent evolution of initial errors. Considering that there exist different types of El Niño events in nature, we choose the reference states with initial time being January, April, July, and October, and denote them as R^i_{Jan}, R^i_{Apr} R^i_{Jul}, and R^i_{Oct}, $i = 1, 2, 3, \ldots$, respectively. For each type of true states, quantities of them have been taken to perform the numerical experiments. Similar results are obtained. For simplicity, we take one representative from each type to present the results. Without loss of generality, they are denoted by R^1_{Jan}, R^1_{Apr}, R^1_{Jul}, and R^1_{Oct}. Figure 1 shows the SSTA components of the four reference states, which are averaged over Niño-3 region and are generally called Niño-3 index. The time-dependent Niño-3 indexes of the true states represent four different El Niño events, with SSTA starting warming respectively in January, April, July, and October. The El Niño events, R^1_{Jan} and R^1_{Apr} tend to peak at the end of the year, while R^1_{Jul} and R^1_{Oct} peak at the end of next year.

[7] In the prediction experiments, lead times are all 12-month. For each of the four reference states, four predictions are made with different start months, which are marked in Figure 1 by dots. For example, in case of R^1_{Jul}, July, October, and January and April in the next year are taken as the start months. Considering that CNOP is the initial error that has largest effect on prediction results [*Mu et al.*, 2003; *Mu and Zhang*, 2006], for each prediction experiment, we calculate the CNOPs of these reference states for the time interval length $\tau = 12$ with the above start months. For convenience, this kind of initial uncertainties are simply called as CNOP-type errors, which are found to locate at the boundary of the constraint condition in the phase space, i.e. $||\vec{u}_0||_1 = \delta$. Some representatives of these CNOPs are shown in Figure 2, where the SSTA and thermocline depth anomaly components are for $\delta = 1.0$. In the rest of this section, we will investigate the season-dependent evolutions of these CNOP-type errors.

3.1. Season-Dependent Behaviors of CNOP-Type Errors

[8] To investigate the seasonal dependence of initial error evolution, a year is divided into four "seasons" starting with January to March (JFM), followed by April to June (AMJ), and so forth. We study the slope κ of curve $\gamma(t) = ||\vec{T}'(t)||_2$ at different seasons, which represents the tendency of initial error growth. A positive (negative) value of κ corresponds to an increase (decrease) of the errors, and the larger the absolute value of κ, the faster the increase (decrease).

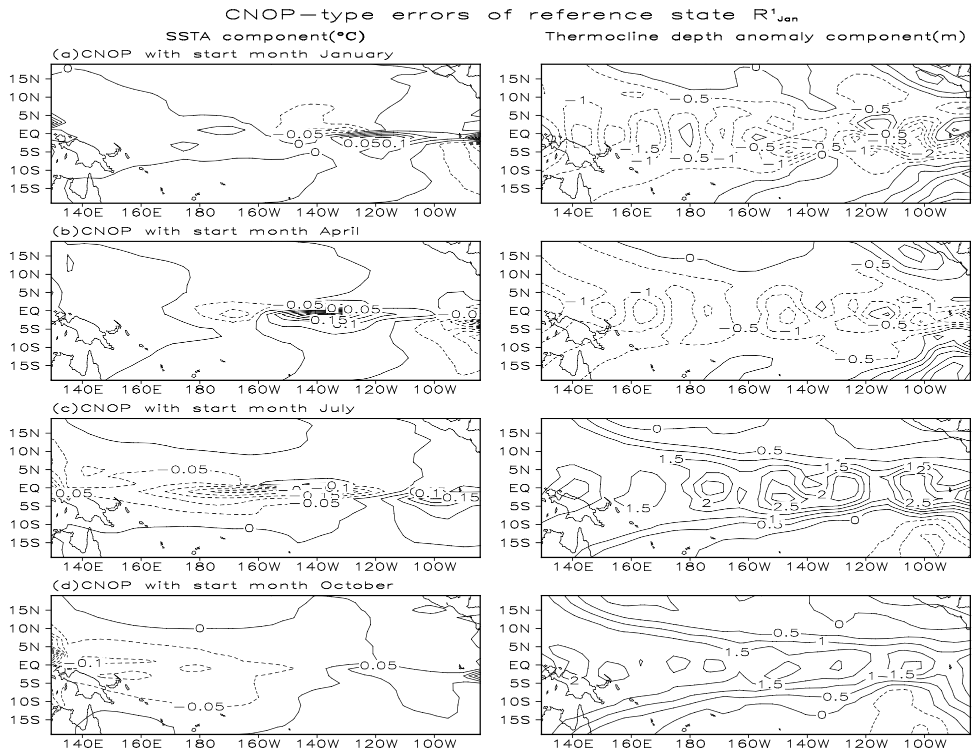

Figure 2. The patterns of CNOP-type error with magnitude of 1.0 (value of δ) for R^1_{Jan}. (left) SSTA and (right) thermocline depth anomaly components for the start month being (a) January, (b) April, (c) July, and (d) October.

[9] Tables 1 and 2 list the slopes κ of CNOP-type error evolutions with start month being October and July for the above reference states (El Niño events). E_{Nino-3} there represents the uncertainties of El Niño prediction with one year lead time (τ = 12 months), which is caused by the corresponding CNOP-type errors and is obtained by subtracting the Niño-3 index of reference states from the predicted one. It is demonstrated that the CNOP-type errors tend to grow aggressively during AMJ for the four types of El Niño events and show apparent season-dependent evolution. From the values of E_{Nino-3} in Tables 1 and 2, it is also clear that CNOP-type errors cause significant prediction uncertainties, which is the largest with the constraint condition from the definition of CNOP.

[10] For the four types of reference states, the season-dependent evolutions of CNOPs with start month January are also investigated (Table 3). The results demonstrate that the significant growth of CNOP-type errors tend to occur during AMJ and JAS with maximum value appearing in JAS. Besides, CNOP-type errors cause the severest prediction uncertainties. Note that although the maximum slopes appear in JAS, the error growth during AMJ have become aggressively large, which could have caused the dramatic decrease of El Niño forecast skill during AMJ. As for the significant error growth of El Niño in JAS, we will discuss it in section 3.2.

[11] We further investigate the evolutions of CNOP-type errors with start month April. In this case, the El Niño events are directly predicted from spring. *Kirtman et al.* [2001] and quite a few authors reported that the forecast starting in this season is relatively easy and there is no notable SPB phenomenon. Our results demonstrate this fact too. Table 4 shows the slopes κ with start month April. It is clear from it that the prediction errors of SSTA (Niño-3 index) caused by CNOP-type errors with start month April are fairly smaller than the corresponding ones with other start months (see the "E_{Nino-3}" in Tables 1–3). Besides, the values of κ tend to attain the largest value during JAS. This is consistent with the results of *Kirtman et al.* [2001]. The decrease of forecast skill in JAS can also be observed from Figure 4 of Kirtman et al., although it is not so significant as that in AMJ of other cases.

[12] From the above results, it is clear that when El Niño events are predicted bestriding next spring from July and October, there exist apparent seasonal dependence of CNOP-type error growth, and the largest growths tend to occur during AMJ. In these two cases, CNOPs cause the severest prediction uncertainties for El Niño, and the dramatic decrease of the skill for El Niño forecast may occur in AMJ due to the considerable error growth, which could then cause the SPB phenomenon. In case of the start month being January, although the largest error growth of El Niño forecast occurs in JAS, the error growth in AMJ has become aggressively large and could have caused the severe

Table 1. Slopes κ of CNOP-Type Error Evolution With $||\vec{u}_0|| \leq$ 1.0 for Start Month October

Reference State	OND	JFM	AMJ	JAS	E_{Nino-3}
R^1_{Jan}	1.3507	2.1358	**6.3777**	1.1392	1.6711
R^1_{Apr}	1.2216	1.6740	**5.0808**	3.5340	2.0953
R^1_{Jul}	2.1358	3.6559	**7.7281**	1.7341	−2.4585
R^1_{Oct}	1.9107	3.5522	**7.6553**	3.1489	−2.7356

Table 2. Slopes κ of CNOP-Type Error Evolution With $||\vec{u}_0|| \leq$ 1.0 for Start Month July

Reference State	JAS	OND	JFM	AMJ	E_{Nino-3}
R^1_{Jan}	2.0843	2.7967	1.4844	**5.6386**	2.3252
R^1_{Apr}	2.4797	**4.6886**	4.0120	1.2780	−1.8365
R^1_{Jul}	2.1575	3.4201	4.6495	**5.1457**	−2.5613
R^1_{Oct}	1.9124	2.7230	1.7919	**5.5768**	2.2174

prediction uncertainties of El Niño forecast bestriding spring. These suggest that CNOP-type errors have the potential for inducing obvious season-dependent evolution related to SPB. Now the remaining question is: are there other kind of initial errors with magnitudes being the same as those of CNOP-type errors in terms of the chosen norm, which have less effects on the prediction results, or have insignificant season-dependent behavior and fail to cause SPB?

[13] To address this question, for the reference states R^i_{Jan}, R^i_{Apr}, R^i_{Jul}, and R^i_{Oct}, we investigate a great deal of initial errors and find that many of them have the less prominent season-dependent evolution and do not cause the severe prediction uncertainties of El Niño. Figure 3 shows four representatives of them for R^1_{Jan}, which are of the magnitude of 1.0 measured by the chosen norm $|| \cdot ||_1$ and simply called Non-CNOP type error. Table 5 lists κ and E_{Nino-3} of such errors and those of CNOP for R^1_{Jan}, where CNOP is also of magnitude of 1.0. It is shown that either there is no significant seasonal dependence of the growth rates of these initial errors, or such errors have no considerable effect on the forecast results, and consequently there is no SPB for El Niño forecast. Comparison of CNOP and Non-CNOP type errors demonstrate that CNOP not only induces the severest prediction uncertainties but also has the prominent season-dependent evolution.

[14] Besides, we also examine the season-dependent evolution of CNOP-type error growth for the neutral year. Our results suggest that in this case the growth of CNOPs does not have obvious seasonal dependence. For simplicity, numerical results are not shown here.

3.2. Implication of Season-Dependent Behaviors of CNOP-Type Errors to SPB

[15] The above results demonstrate that not only CNOP-type error induces the severest prediction uncertainties of El Niño, but also its evolution shows the prominent seasonal dependence. Naturally, it is closely related to the problem of SPB, which is generally referred to that the forecast skill of ENSO declines dramatically during spring (April-May). Our results demonstrate this fact from the point of view of initial error growth. For the start month being July and October, the growth rates of CNOP-type errors for the four types of El Niño events tend to be the maximum during AMJ, which coincides the time of predictability barrier documented in observations as well as CZ model runs.

[16] For the start month being January, our results show that the significant error growths of four types of El Niño events tend to start in AMJ and to be the largest in JAS. By investigating the LDEO1 version of CZ model, *Kirtman et al.* [2001] showed that the correlation coefficients of SSTA (Niño-3 index) forecast initialized in January decrease from 0.7 to 0.4 during AMJ [see *Kirtman et al.*, 2001, Figure 4], while the tendency of the correlation change during JAS cannot be drawn clearly. Thus, the question is why there exists this difference. A possible explanation follows. When the El Niño is predicted bestriding spring (AMJ), the skill of El Niño forecast has decreased dramatically and become very small due to the significant error growth in AMJ. Then there is no more space for remarkable declination of the correlation coefficient during JAS even if the errors grows considerably in this period. The second possible explanation is that our results are based on El Niño year, while *Kirtman et al.* [2001] did not distinguish El Niño year from non-El Niño year and considered the collective of El Niño, La Niña and neutral years, which is different from that of our study. Besides, the predictability measurements adopted in these two studies are also different, which may cause some difference between the results. Thirdly when *Kirtman et al.* [2001] calculated the correlation coefficient between prediction and observation, the influence of model error are included, while our results are based on the assumption of perfect model and we do not consider the effect of model error on SPB. This also has possibility for causing some differences between the results of two studies. Of course, whether the model error has influence on predictability barrier is an unresolved problem, which might stimulate further investigation on SPB. On all accounts, the main results of this study coincide with those of *Kirtman et al.* [2001], and there is no essential contradiction.

4. Summary and Discussion

[17] The main results of this short paper are as follows. There exist some kinds of initial errors represented by conditional nonlinear optimal perturbations, which yield prominent season-dependent evolution, cause the severest prediction uncertainties and are then closely related to spring predictability barrier (SPB) for El Niño. On the other hand, there are some other kinds of initial errors, which have no considerable seasonal dependent evolution in spite of the fact that the magnitudes of these errors are the same as those of CNOPs. Furthermore, the prediction uncertainties caused by these initial errors are of little significance. These results provide a clue to understand why SPB occurs

Table 3. Slopes κ of CNOP-Type Error Evolution With $||\vec{u}_0|| \leq$ 1.0 for Start Month January

Reference State	JFM	AMJ	JAS	OND	E_{Nino-3}
R^1_{Jan}	0.8481	**4.1740**	**8.8463**	0.4555	−2.3865
R^1_{Apr}	0.8218	1.7353	**3.9384**	2.9960	1.8221
R^1_{Jul}	1.0103	**3.6650**	**4.6170**	1.7049	2.0860
R^1_{Oct}	1.0376	**5.7698**	**8.5371**	−0.8441	−2.4281

Table 4. Slopes κ of CNOP-Type Error Evolution With $||\vec{u}_0|| \leq$ 1.0 for Start Month April

Reference State	AMJ	JAS	OND	JFM	E_{Nino-3}
R^1_{Jan}	1.9335	5.4887	**7.9286**	−3.9022	−1.2262
R^1_{Apr}	2.7136	**6.1334**	5.0128	−1.9121	−1.6298
R^1_{Jul}	2.3528	**5.3071**	3.0262	1.4047	1.5615
R^1_{Oct}	2.6583	**6.2192**	5.6644	−3.6234	−1.2341

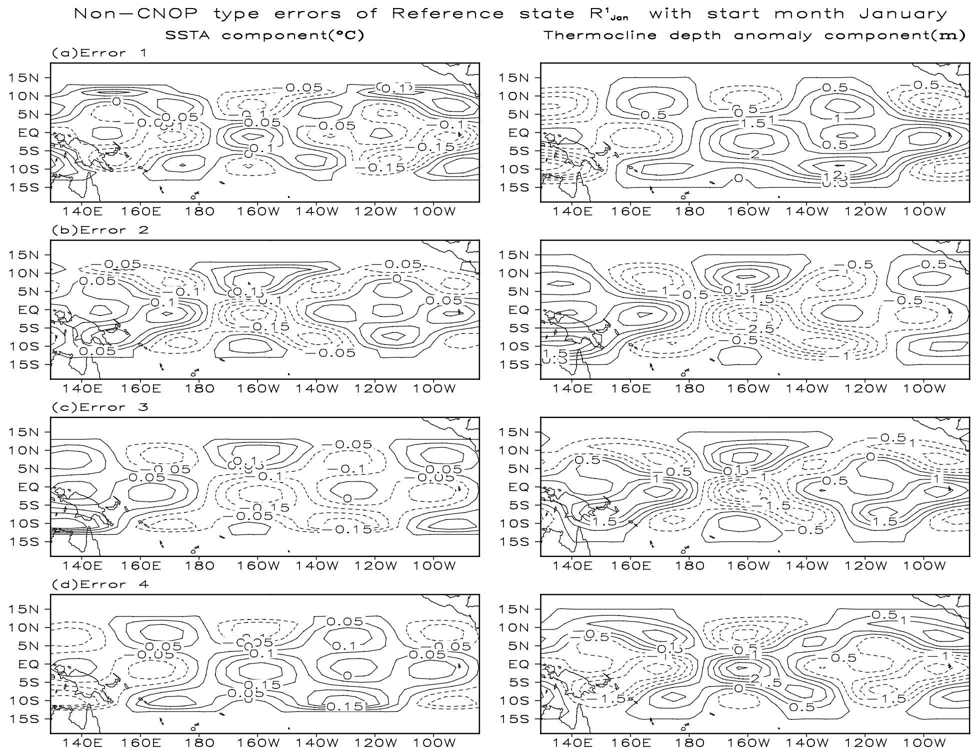

Figure 3. Four representatives of Non-CNOP type errors with magnitude of 1.0 for R^1_{Jan}, where the start month of prediction is January. (left) SSTA and (right) thermocline depth anomaly components.

in some ENSO predictions, and *Chen et al.* [2004] claimed that the SPB in their ENSO prediction experiments are not as severe as that in other forecast models. The study of this paper also indicate the importance of data assimilation in ENSO prediction. Besides, considering that the pattern of CNOPs might represent the "sensitive area", it suggests that intensifying observations in such areas might be of importance to increase the ENSO prediction skill by the reduction of SPB.

[18] In this study, we investigate the evolutions of initial errors for the individual El Niño events of representative types with different onset months. Since the main characteristics of La Niña events, e.g. phase-locking, cannot be well modelled by CZ model [*An and Wang*, 2001], no attempt has been made in this paper to study the corresponding problem for La Niña. The correlation coefficients obtained from *Kirtman et al.* [2001] are essentially a statistical index of the predictions of El Niño and La Niña events and neutral case for a period of about 20 years. Obviously, we can not expect that the results of these two approaches are the same. Nevertheless, the main results of this paper support those of *Kirtman et al.* [2001].

Table 5. κ of Initial Errors (Norm Magnitude 1.0) With Start Month January for R^1_{Jan}

Error Type	JFM	AMJ	JAS	OND	E_{Nino-3}
CNOP	0.8481	4.1740	**8.8463**	0.4555	−2.3865
Non−CNOP 1	−0.4929	0.2541	0.1709	−0.2311	−0.0757
Non−CNOP 2	−0.5411	0.1659	0.1831	−0.1795	0.0351
Non−CNOP 3	−0.4126	−0.0708	0.3766	0.0625	0.0853
Non−CNOP 4	−0.3887	−0.1195	0.3523	0.1517	−0.1252

[19] The results in this paper suggest that SPB can be caused by some kinds of initial errors, and CNOP could be one of such errors. Besides, other kinds of initial errors, i.e. Non-CNOP type errors, will not cause SPB. These new findings encourage us to improve ENSO prediction skill by data assimilation or (and) targeting observations.

[20] SPB is one of the unresolved problems for ENSO. This study are on seasonal dependence of error growth and stand for a step to study SPB using CNOP. It is expected that the future work can address the following issues: The first question is whether the results obtained in this paper is model dependent. Secondly, are the SPB reported in other papers [e.g., *Kirtman et al.*, 2001] caused only by initial errors? Thirdly, are there considerable differences among the errors evolutions of El Niño, La Niña, and neutral years? Finally, if SPB is caused by the CNOP-type or other kind of errors, what is the mechanism responsible for that? All these questions deserve our future studies.

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