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Progress in Predictability Studies in China (2003–2006)

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ABSTRACT

Since the last International Union of Geodesy and Geophysics General Assembly (2003), predictability studies in China have made significant progress. For dynamic forecasts, two novel approaches of conditional nonlinear optimal perturbation and nonlinear local Lyapunov exponents were proposed to cope with the predictability problems of weather and climate, which are superior to the corresponding linear theory. A possible mechanism for the "spring predictability barrier" phenomenon for the El Niño-Southern Oscillation (ENSO) was provided based on a theoretical model. To improve the forecast skill of an intermediate coupled ENSO model, a new initialization scheme was developed, and its applicability was illustrated by hindcast experiments. Using the reconstruction phase space theory and the spatio-temporal series predictive method, Chinese scientists also proposed a new approach to improve dynamical extended range (monthly) prediction and successfully applied it to the monthly-scale predictability of short-term climate variations. In statistical forecasts, it was found that the effects of sea surface temperature on precipitation in China have obvious spatial and temporal distribution features, and that summer precipitation patterns over east China are closely related to the northern atmospheric circulation. For ensemble forecasts, a new initial perturbation method was used to forecast heavy rain in Guangdong and Fujian Provinces on 8 June 1998. Additionally, the ensemble forecast approach was also used for the prediction of a tropical typhoons. A new downscaling model consisting of dynamical and statistical methods was provided to improve the prediction of the monthly mean precipitation. This new downscaling model showed a relatively higher score than the issued operational forecast.

Key words: predictability, prediction, perturbation, weather, climate

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1. Introduction

Predictability is a fundamental issue in both atmospheric and oceanic research and numerical weather and climate prediction. Studies on predictability have received considerable attention in recent decades due to the pioneering work of the atmospheric scientist Lorenz in the early 1960s (Lorenz, 1962, 1963, 1965, 1969).

One of the great efforts is the exploration of the fundamental limits to predictability (Smith et al., 1999). The predictability of a system is strongly dependent on its stability properties (Moore and Kleeman, 1996; Smith et al., 1999). If the system is particularly unstable, any initial uncertainty that projects significantly onto one of these instabilities will severely limit the skill of an initial-value forecast. Lorenz (1975) showed that the extreme sensitivity of weather predictions to initial conditions means that detailed forecasts are, in general, impossible beyond about 2 weeks. This kind of initial-value problem is referred to as the first kind of predictability problem (Lorenz, 1975). In the studies of the first kind of predictability problem, the models are usually assumed to be perfect. Generally, medium-range weather forecasts with atmospheric models and seasonal forecasts with coupled ocean-atmosphere models are considered to fall under this scenario (Palmer, 1996). The second kind of predictability problem aims to estimate how a given dynamic system responds to a change in some prescribed

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parameter or external forcing (Lorenz, 1975). The response of the El Niño-Southern Oscillation (ENSO) to the stochastic forcing related to the Madden-Julian Oscillation (MJO), westerly burst events, etc., or the response of an atmospheric general circulation model (GCM) to a prescribed change in sea surface temperatures (SSTs), are all problems of the second kind of predictability. Uncertainties in such predictions may arise from the accuracy in the prescribed change itself, or from uncertainties in model formulation. In practice, many forecasts do not fall exclusively into either of these two categories. Even though problems of the second kind of predictability are, by construction, not sensitive to initial conditions, the underlying instabilities of the flow play an important role in determining the associated predictability.

Both model error and initial uncertainties can cause the prediction error, but it is difficult to separate their relative contributions. Additionally, the complexities and the nonlinearities of atmospheric and oceanic motions also limit the exploration of predictability. Nevertheless, within the frame of the two kinds of predictability problems proposed by Lorenz (1975), some studies on predictability have been conducted. They can be grouped into two types: the analysis of the factors and mechanisms that cause forecast uncertainties, and the search for methods and approaches to reduce these uncertainties.

In the predictability studies, three approaches have been used. The first approach is the dynamic method, which investigates the evolution of initial errors by numerical models. The Lyapunov exponents (Oseledec, 1968) and linear singular vector (LSV) (Lorenz, 1965) techniques are two examples. The second approach is the statistical method. It calculates the variance of a time series or the correlation coefficients of the forecast results and observations, or determines the evolution of the difference between two "analogous" states from historical data (Lorenz, 1969). The third approach is the mixture of the statistical and dynamic methods (Lorenz, 1969).

To reduce the prediction errors caused by initial uncertainties, a statistical prediction involving an ensemble of possible projections has become commonplace in weather and climate prediction since Leith in the early 1970s (Leith, 1974). Another effective approach is variational data assimilation, which may be the most effective technique for improving initial analysis fields for model prediction. For the prediction uncertainties caused by model error, multi-model ensemble forecasts could be a useful approach (Palmer et al., 2004).

By using the above approaches, scientists obtained many instructive results during the last few decades. Lorenz (1962, 1963) discovered the upper limit of about two weeks for weather predictability. Webster and Yang (1992) demonstrated the "spring predictability barrier" (SPB) of ENSO forecasts by analyzing the correlation between El Niño and the Southern Oscillation. Samelson and Tziperman (2001) showed the growth-phase predictability barrier of El Niño. Recently, Chen et al. (2004a) performed hindcast experiments and successfully hindcasted two years of SST anomalies.

Chinese scientists have also made some significant contributions to predictability studies. Chou (1989) used a cell-to-cell mapping theory to obtain the global predictability limit of a system. Li (2000), Li et al. (2000), and Li et al. (2001) demonstrated the dependence of the model predictability time on the machine precision and the model itself. Li (2000) and Li et al. (2001) also provided an optimal numerical integration method of step-step adjustment and made the numerical model achieve the best predictability. Based on the two kinds of predictability problems (Lorenz, 1975), Mu et al. (2002) classified three predictability problems in numerical weather and climate prediction, i.e., maximum predictability time, maximum prediction error, and maximum allowable initial error. To explore the impact of nonlinearity on predictability, Mu (2000) and Mu and Wang (2001) proposed the concept of nonlinear singular vector and nonlinear singular value. Recently, Chou (2002) and Li and Chou (2003) established the monotonicity principle of predictability.

Since the last International Union of Geodesy and Geophysics (IUGG) General Assembly in 2003, four years have passed. During this period, Chinese scientists have made further progress in the study of predictability. In this paper, we briefly review this progress.

2. Predictability in dynamical forecasts

2.1 *Theoretical studies*

2.1.1 *Conditional nonlinear optimal perturbation*

The LSV is the fastest growing perturbation of a linear model, and techniques employing this concept have been widely used in predictability studies (Lorenz, 1975). However, the LSV is always associated with the sufficiently small initial perturbations (Oortwijin and Barkmeijer, 1995; Mu et al., 2003). Considering this limitation of the LSV in revealing the effect of nonlinearity on predictability, Mu (2000) provided an approach of nonlinear singular vector (NSV). Given the initial observation, the nonlinear optimal perturbations should be less than an upper bound of

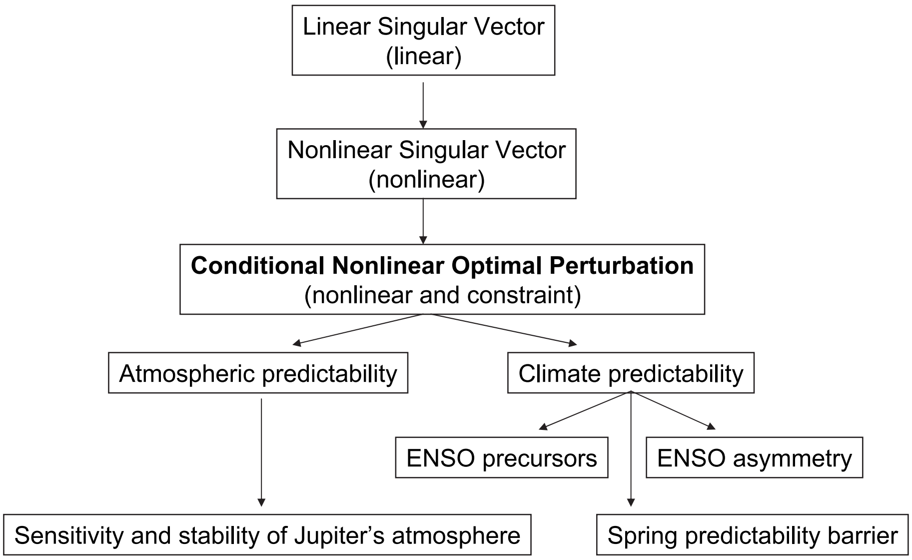

Fig. 1. Diagram showing conditional nonlinear optimal perturbation and its applications in predictability studies.

initial observational error. However, Mu and Wang (2001) found that there exists local NSVs, which could exceed the upper bound. To overcome this weakness, Mu et al. (2003) further proposed a new approach of conditional nonlinear optimal perturbation (CNOP) to address the predictability problems (see Fig. 1).

CNOP is an initial perturbation whose nonlinear evolution attains the maximum value of a given cost function at prediction time (Mu et al., 2003; Mu and Duan, 2003), where the cost function measures the evolution of initial perturbations in terms of the chosen measurement (for example, a norm $\| \cdot \|$). Mathematically, it is the global maximum of the cost function. In some cases, there exists local maximum values and the corresponding initial perturbations are called local CNOPs.

The computation of CNOP is related to a nonlinear optimization problem, so it is difficult to solve it analytically. Mu et al. (2003), Duan et al. (2004), Mu et al. (2004), and Sun et al. (2005) used some simple models consisting of sets of ordinary differential equations (ODEs) and solved the corresponding CNOPs numerically. Some common characteristics of CNOPs were found. First, when the linear approximation of a nonlinear model is not valid, CNOPs are significantly different from LSVs, and cannot be approximated by LSVs. Second, the (global) CNOPs and local CNOPs are all located on the boundary of the domain defined by the given constraint. These characteristics may be intrinsic for CNOPs.

To test the intrinsic properties of CNOPs, Mu and Zhang (2006) employed a two-dimensional quasi-geostrophic model consisting of a partial differential equations to compute the CNOPs. The results demonstrated that when the initial perturbations were large, or the time periods were long, or both, CNOPs and LSVs shows remarkable differences. First, LSVs represent the optimal growing direction, while CNOPs represent a kind of initial perturbation that has the largest effects on the predictability. That is to say, CNOP is only a "pattern" rather than a "direction" due to the nonlinearity in the model. Consequently, when the linearized model is not a good approximation to the corresponding nonlinear model, the CNOPs and the corresponding LSVs are remarkably different for a long time or/and a finite magnitude of the initial perturbation. In addition, the differences between CNOPs and LSVs were also shown by investigating their dynamical evolutions. When the initial perturbations are sufficiently small, the evolutions of LSVs and CNOPs are only trivially different. With the increasing magnitudes of initial perturbations, the differences between the linear and nonlinear evolution of both CNOPs and LSVs and those between the nonlinear evolution of CNOPs and the linear evolution of LSVs become larger. Second, Mu and Zhang (2006) illustrated that the CNOPs of the quasi-geostrophic model are located at the boundary of the constraint. Thus, Mu and Zhang (2006) verified the results of simple models with respect to CNOP by a realistic model. Mu and Zhang (2006) therefore implied the feasibility of the CNOP approach in realistic numerical models.

The researches discussed above has demonstrated that the distinct feature of the CNOP approach lies in its applicability in revealing the effect of nonlinearity on predictability, making it superior to the LSV

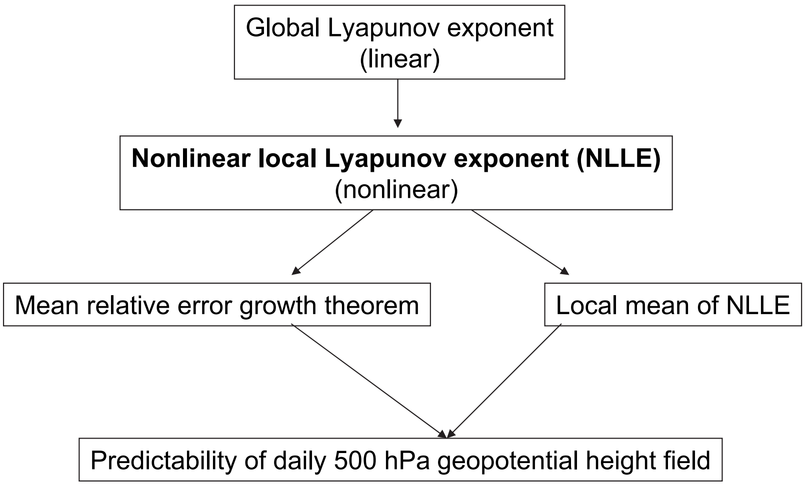

Fig. 2. Same as Fig. 1 except for nonlinear local Lyapunov exponent.

approach. It is expected that CNOP can be widely used in studies of atmospheric and oceanic sciences. Considering the application of LSV to ensemble forecast and target observation, we should also explore the applicability of the CNOP approach in these fields.

2.1.2 *Error growth*

As mentioned in the introduction, the atmosphere itself is a complex nonlinear system. There exist many limitations in using the linear theory of error growth to study atmospheric predictability (Lacarra and Talagrand, 1988; Mu, 2000). It is therefore necessary to develop a nonlinear theory for quantifying error growth. Upon this request, Li et al. (2006) and Ding and Li (2007) introduced a novel concept of nonlinear local Lyapunov exponent (NLLE) (see Fig. 2). The NLLE generalized the linear theory of Lyapunov exponents to the nonlinear field. Due to the effect of nonlinearity, the NLLE depends on initial states, initial errors and the time intervals, and is therefore quite different from the global (and local) Lyapunov exponent. These characteristics of the NLLE approach may demonstrate its advantages.

By using the NLLE, Ding and Li (2007) presented a saturation theorem of mean relative growth of initial error (RGIE). That is, for a chaotic system, the mean RGIE will certainly reach a saturation value in a finite time interval. Also, they demonstrated that the average predictability limit of a chaotic system could be quantitatively determined as the time when the mean RGIE reaches its saturation level. To measure the predictability of a given state with certain initial uncertainties, the concept of the local ensemble mean of the NLLE was also given to quantify the local average predictability limit of a chaotic system.

The NLLE was also used by Chen et al. (2006) to investigate the predictability of the daily 500 hPa geopotential height field. The results showed that the predictability of the daily 500 hPa geopotential height field has a zonal belt distribution with the maximum predictable time about 12 days over the tropics, the second belt of about 8–9 days over the Antarctic, the third belt of about one week over the Arctic, and the minimum about 3–4 days in the subtropics and middle latitudes. Additionally, they demonstrated that atmospheric predictability varies with the seasons. For most regions in the Northern Hemisphere, the predictability in winter is higher than that in summer.

The NLLE is a new idea for predictability studies. There is much work including the theory itself awaiting further investigation.

2.2 *Applications of CNOP to atmosphere predictability*

Jiang (2006) used the CNOP approach to study the stability and sensitivity of small-scale vortices motions in Jupiter's atmosphere. With a two-layer quasi-geostrophic model and its adjoint model, Jiang (2006) solved the CNOPs related to Jupiter's atmospheric motions and compared them to the corresponding LSVs. The results showed that CNOPs can capture the nonlinear characteristics of small-scale vortices motions in Jupiter's atmosphere and showed significant differences from LSVs for large initial perturbations. Besides, in some basic states, local CNOPs were also found. These results demonstrated the effect of nonlinearity on Jupiter's atmospheric motion. Jiang (2006) thought that the application of the CNOPs to the theoretical models of small-scale vortex motions in Jupiter's atmosphere may provide the chance for comparing the stability of Jupiter's atmospheric motions and the Earth's atmospheric motions, which may help

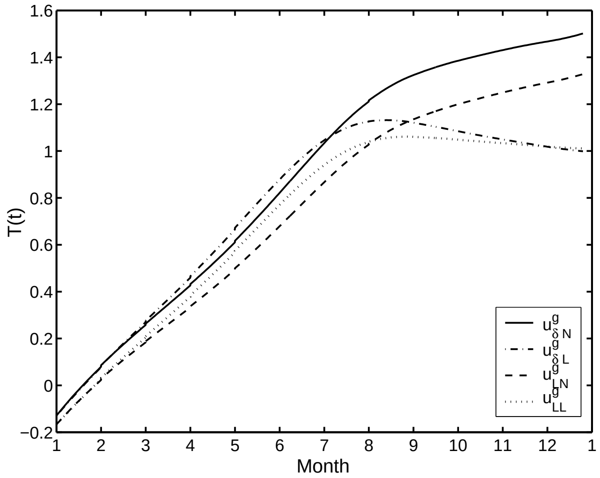

Fig. 3. Nonlinear and linear evolutions of the nondimensional model variable T (SSTA) corresponding to CNOP and LSV of the annual cycle, respectively. $u^g_{\delta N}$ (u^g_{LN}) and $u^g_{\delta L}$ (u^g_{LL}): the nonlinear and linear evolutions of SSTA of the CNOP (the LSV), which are two El Nino events. CNOP acts as the optimal precursor for El Nino (from Duan et al., 2004)

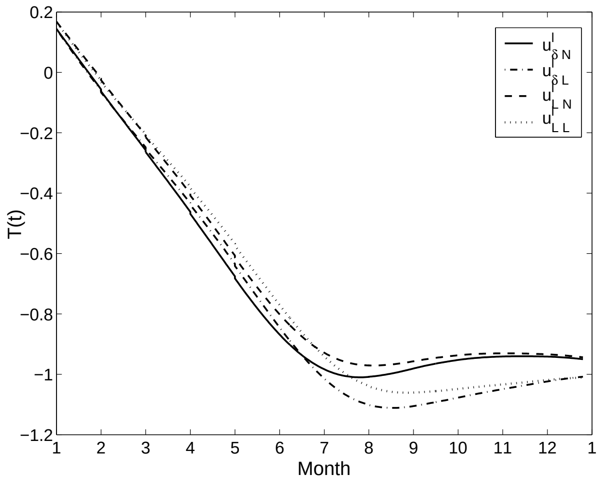

Fig. 4. Same as Fig.1 except for La Niña events related to the local CNOP (the corresponding LSV) (from Duan et al., 2004).

us to further understand the laws of Earth's atmospheric motions.

2.3 *Applications of CNOP to ENSO forecasts*

2.3.1 *The optimal precursors for ENSO*

Moore and Kleeman (1996) and Thompson (1998) demonstrated that it is of great significance to find out the precursors for ENSO events for improving ENSO predictability. They used the LSV approach to identify the optimal growing initial pattern for ENSO, i.e., the optimal precursors. However, as mentioned above, LSV has limitations for revealing nonlinearity. Considering this point, Duan et al. (2004) employed CNOP to study the optimal precursors for ENSO events with the coupled model of Wang and Fang (1996) (WF96). It was shown that the CNOP of the annual cycle evolves into the positive SST anomaly nonlinearly, which has a striking resemblance to the development of El Niño and, therefore, acts as a precursor for the El Niño event in the WF96 model. Although the corresponding LSV also develops into an El Niño, the intensity is considerably weaker than that of CNOP (see Fig. 3). In this sense, CNOP was regarded as the optimal precursor for El Niño by Duan et al. (2004). For the local CNOP of the annual cycle, Duan et al. (2004) showed that it acts as the optimal precursor of the La Niña events (Fig. 4). In addition, Duan et al. (2004) found that when using LSV to study the intensity of ENSO events, the corresponding El Niño and La Niña events in the linearized model are of the equal amplitude, the El Niño and La Niña events are symmetric in amplitude (Fig. 5). In the CNOP approach, the El Niño event is obviously stronger than the La Niña event under the condition that the (global) CNOP and local CNOP are of the same large amplitude (Fig. 5), which is consistent with the observed ENSO asymmetry after 1976. So they demonstrated that the linear theory of singular vector cannot reveal the nonlinear asymmetry of El Niño and La Niña. It is therefore indicated that ENSO asymmetry may be caused by the nonlinear feedback mechanism of the coupled ocean-atmosphere.

The results discussed above involved the ENSO amplitude asymmetry after the 1970s. Duan and Mu (2006) further investigated the change of the ENSO amplitudes asymmetry before and after the 1970s. They showed that the ENSO asymmetry had become considerably larger since the 1976 climate shift. Considering how the tropical background field modulates the ENSO cycle, Duan and Mu (2006) explored the effect of the climatological basic-state change on the ENSO asymmetry by applying the approach of CNOP in a theoretical coupled model. They reproduced the observed decadal change of the ENSO asymmetry qualitatively. Based on the physics described by the model, the mechanism of the ENSO asymmetry change on the inter-decadal scale was explored by Duan and Mu (2006). They demonstrated that the decadal change of the ENSO asymmetry may be induced by the changing nonlinear temperature advection, which is closely related to the decadal change of the tropical background state. Then Duan and Mu (2006) indicated that the decadal change of ENSO

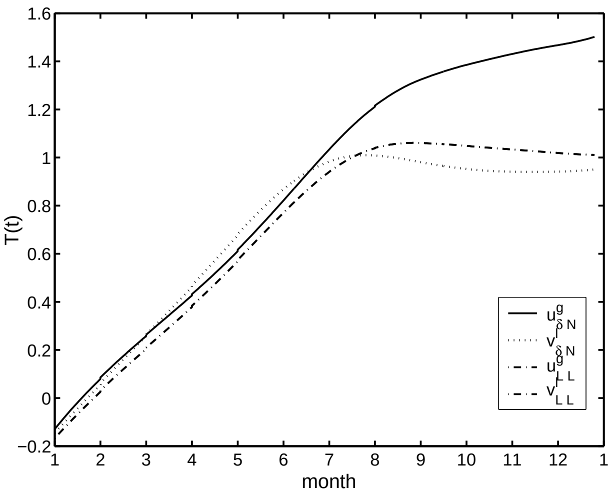

Fig. 5. Comparisons between El Niño and La Niña amplitudes. $u^g_{\delta N}$ (u^l_{LL}): SSTA nonlinear (linear) evolution of CNOP (the corresponding LSV); $v^l_{\delta N}$ (v^l_{LL}): nonlinear (linear) evolution of $-T$ (negative anomaly of SST) of local CNOP (the corresponding LSV), indicating the amplitude of La Niña events (from Duan et al., 2004).

asymmetry may result from the combined effect of the changes of the tropical background state and the nonlinearity.

In view of the simplicity of the WF96 model, an intermediate coupled ENSO model of Zebiak and Cane (1987) (CZ model) was also used to investigate the precursors for ENSO (Xu, 2006). The numerical experiments demonstrated that the CNOPs of the climatological basic-state annual cycle, rather than LSVs, act as the optimal precursors of ENSO, whose configuration of SST anomalies and thermocline depth anomalies reveals the fact that the transition phase of thermocline depth displacement leads to the SST variation and supports the results of Duan et al. (2004). Then the results obtained by the CZ model further showed the spatial structure of the CNOP and emphasized the locality of optimal precursors for ENSO in space distribution.

2.3.2 *"Spring predictability barrier" for ENSO events*

Considering that many state-of-the-art coupled ocean-atmosphere models have particular difficulty predicting ENSO prior to boreal spring and the causes of this spring predictability barrier (SPB) remain controversial and elusive, Mu et al. (2007a) used the WF96 model to investigate the problem from the point of view of initial error growth associated with ENSO anomalies using the CNOP approach. The results showed that the largest growth rate of the CNOP for El Niño occurs in boreal spring during the onset of the ENSO warm event, which coincides with the time of the SPB in ENSO models. With increasing magnitudes of CNOPs, the amplitude of spring error growth for El Niño becomes progressively larger. Although the largest error growth of El Niño in spring during the onset of ENSO warm events is also shown through LSV, the CNOP growth is significantly larger than the corresponding LSV growth for large-amplitude initial perturbations. This has the implication that the nonlinearity plays an important role in the error growth of the ENSO warm event. Furthermore, Mu et al. (2007a) compared the seasonal variations of the CNOP growth for ENSO events with those of a large ensemble of initial errors chosen randomly from a constrained initial domain. It was demonstrated that not all initial errors tend to induce prominent seasonal variations of error growth, it is the CNOP of El Niño that exhibits the most prominent seasonal variation. But for the La Niña events, even if the initial errors are taken to be of the types of CNOPs, their evolutions do not tend to exhibit the prominent seasonal dependence. Therefore, Mu et al. (2007a) concluded that the seasonal variation of error growth for El Niño may result from the combined effect of the climatological mean state, the El Niño event itself, and the initial error, which is different from the conclusions of previous studies. These studies either emphasized the role of the climatological annual cycle (Moore and Kleeman, 1996; Chen et al., 1997), or demonstrated that of El Niño itself (van Oldenborgh et al., 1999), and did not consider the effects of initial uncertainties. Thus, Mu et al. (2007a) not only pointed out the importance of the initial error pattern in SPB, but also emphasized the combined effect of these three factors on SPB.

In addition, Mu et al. (2007b) used the CZ model to test the results of the WF96 model with respect to SPB. The results supported those of the WF96 model. Furthermore, they found that the CNOP-type error of SST anomaly component of El Niño events tends to centralize locally in the equatorial central and eastern Pacific (Fig. 6). This indicates that the observation accuracy of this region may be important for reducing the uncertainty of ENSO prediction.

It is CNOP that induces the most prominent predictability barrier of ENSO (Mu et al., 2007a,b). If an initial error is not of the type of CNOP, the ENSO prediction may be less uncertain. Therefore, Mu et al. (2007a,b) suggested that if a data assimilation method or/and target observation could filter the CNOP-type initial errors, ENSO predictability could be improved. Of course, these results were derived from the simple models by investigating the dynamic behavior of initial uncertainties. It is expected that the effect of model uncertainties on SPB will be studied in the future.

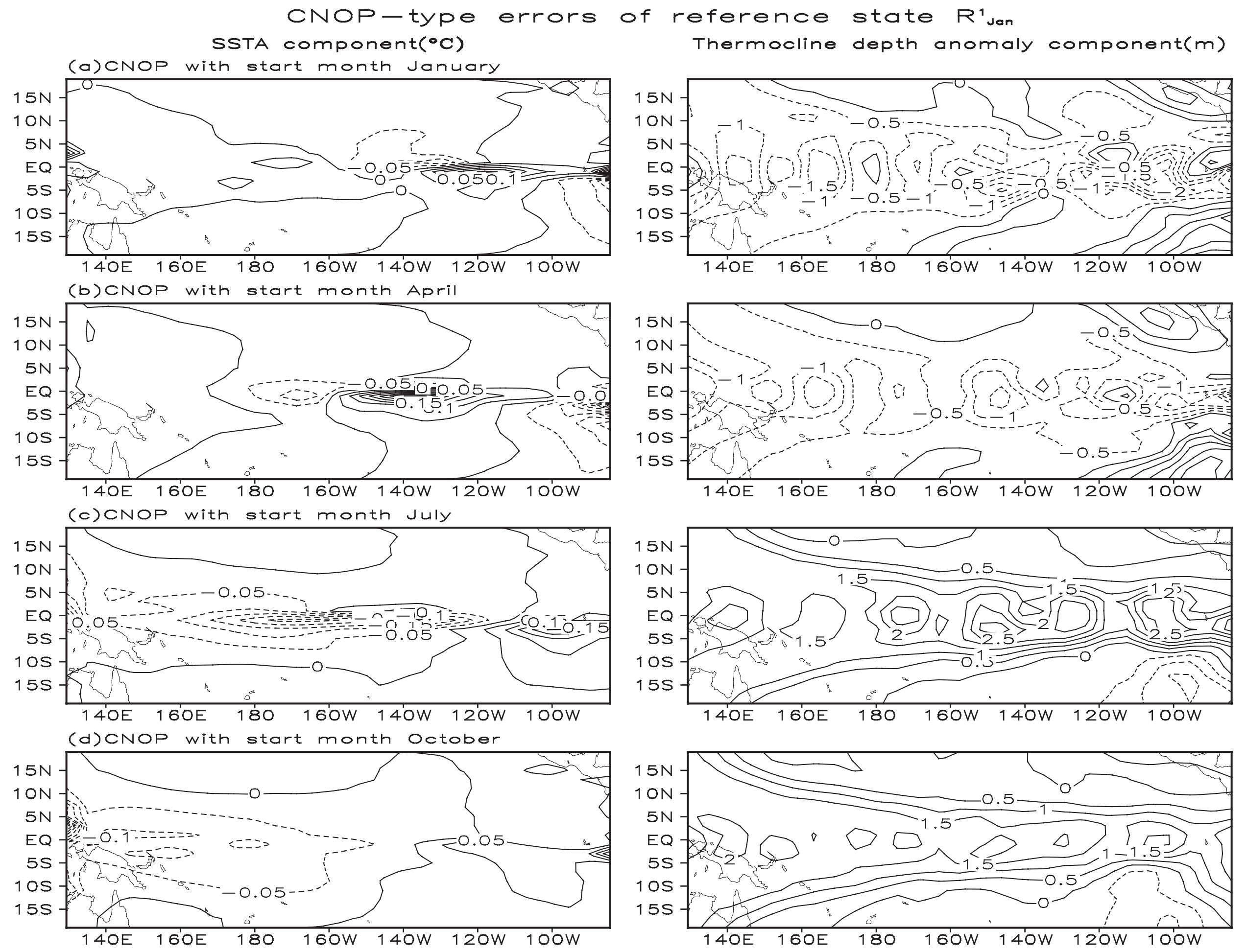

Fig. 6. The patterns of CNOP-type error for a given basic-state El Niño. In the left (right) column are SSTA (thermocline depth anomaly) components for the start months being (a) January, (b) April, (c) July, and (d) October (from Mu et al., 2007b).

2.4 *Predictability of seasonal and monthly forecasts*

Duan and Mu (2005) used a nonlinear optimization method (Mu et al., 2002) to investigate the predictability of a numerical model for ENSO. A lower bound of maximum predictability time for the model ENSO events, an upper bound of maximum prediction error, and a lower bound of maximum allowable initial error were established based on the model. All of them potentially quantified the predictability of ENSO in an adopted model. The numerical results revealed the phenomenon of SPB for the model ENSO event and supported the previous views on SPB.

It had been demonstrated that the intermediate couple model (ICM) developed by Keenlyside and Kleeman (2002) (KK2002) was able to predict ENSO at a 6-month lead time with an initialization scheme (Zhang et al., 2003). To further improve the forecast of this ICM, Zheng et al. (2006) developed a new initialization procedure, which was designed by considering both the magnitude of the nudging parameter and the duration of the assimilation, and then running the coupled model with SST anomalies (SSTAs) nudged to the observations to generate the initial conditions for the atmosphere and ocean. Two sets of hindcasts experiments were performed to test the advantage of the initialization. The numerical results demonstrated that the initialization scheme can generate realistic thermal fields and surface dynamic fields in the equatorial Pacific. Then the prediction ability of the KK2002 model was increased beyond that demonstrated by Zhang et al. (2003). Additionally, by an idealized experiment, Zheng et al. (2006) obtained the optimal nudging parameters that include nudging the intensity and nudging the time length. The twelve-month-long hindcast experiments for the periods of 1984–2003 and 1997–2003 further demonstrated the superiority of the new initialization.

For seasonal predictability, the contribution of initial atmospheric conditions to model skill were generally neglected, or the integrations started from several initial atmospheric fields and were forced by many years of observational SST (Sugi et al., 1997; Rowell, 1998; Kumar, 2003). Consequently, the corresponding seasonal predictability as well as inter-seasonal predictability differences may be underestimated or indefinite. To explore the effect of initial atmospheric conditions on model forecast skill, Lang and Wang (2005) used the real-time initial atmospheric data to the IAP9L-AGCM (9-level global atmospheric GCM developed at the Institute of Atmospheric Physics, Chinese Academy of Sciences) and investigated the model potential predictability of the seasonal mean climate and its response to the strong SSTA signal in both the Niño-3 region and the North Pacific (NP). There are slight inter-seasonal differences in the model potential predictability in the tropics. In northern middle and high latitudes, the prediction skill of IAP9L-AGCM is low in spring and relatively high either in summer for surface air temperature and middle and upper tropospheric geopotential height, or in winter for wind and precipitation. Lang and Wang (2005) also demonstrated that in different regions, the prediction skill of the model is also different. Generally, the model prediction skill rises notably in western China, especially in northwestern China, when SSTA signals in the Niño-3 region are considerably stronger. If one predicts summer climate in the other regions of China, attention should also be paid to the SSTA in the NP.

In Lang and Wang (2005), a comparison between the results of IAP9L-AGCM and those of Sugi et al. (1997) based on an atmospheric model intercomparison (AMIP)-type simulation was also performed. For the seasonal mean surface air temperature (SAT) over eastern Asia, the predictability of IAP9L-AGCM is greater than that demonstrated in Sugi et al. (1997). And for the seasonal mean 500 hPa geopotential height (H500), the predictability of IAP9L-AGCM in the region from 30°–60°N during December-January-February and to the north of 30°N during June–July–August is higher than that suggested by Sugi et al. (1997).

For monthly scale predictability, considering that the zonal mean circulation errors can cause significant forecast errors in the numerical prediction model (Saha, 1992; Baumhefner, 1996), Chen et al. (2003a) developed a new approach to improve the dynamic extended-range (monthly) prediction. First, the monthly pentad-mean nonlinear dynamic regional prediction model of the zonal-mean height field was developed by employing the reconstruction phase space theory and the spatio-temporal series predictive method. Then the resultant zonal height was transformed to its counterpart in the numerical model and was further used to correct the numerical model prediction during the integration process. Thus, the two different kinds of prediction approaches were combined. The numerical experiments showed that this hybrid approach not only reduced the systematic error of the numerical model, but also improved the forecast of the non-axis symmetric components due to wave-flow interaction. This hybrid approach was used to conduct the forecast experiments of zonal mean flow (Chen et al., 2004b). For the 12-month forecast experiments of 1996, the results of the nonlinear model are better than those of persistent climate prediction and the T42L9 model either over the high- and mid-latitude areas of the Northern and Southern Hemisphere, or over the tropical area. The monthly-mean height root-mean-square (RMS) error of the T42L9 model decreased considerably by 30.4% over the high- and mid-latitudes of the Northern Hemisphere, 26.6% over the high- and mid-latitudes of the Southern Hemisphere, 82.6% over the tropics, and 39.4% over the globe. By nonlinear correction after integration, the corresponding anomaly correlation coefficients over the four areas were respectively increased from 0.306 to 0.312, from 0.304 to 0.429, from 0.739 to 0.746, and from 0.360 to 0.400 (a relative change of 11.0% averaged over the globe). Therefore, Chen et al. (2004b) considered that the forecasts produced by the nonlinear model provide more useful information than those of the T42L9 model.

3. Predictability in statistical forecasts

In climate prediction, many studies demonstrated that the SST change can predetermine the tendency of climate change and play an important role in the prediction of drought and floods (Huang et al., 1999; Chen et al., 2002). However, there are still two issues to be addressed. One is to what extent the SSTs predetermine China's precipitation, and the other is whether there exists a spatio-temporal distribution pattern of precipitation. To explore these two questions, Yan et al. (2003) investigated the impact of Pacific SST variations on precipitation predictability in China, where the monthly precipitation data from 160 stations from the National Climate Center and the Pacific SSTs were used. The results showed that the effects of SSTs on precipitation have obvious spatial and temporal distribution features. Temporally, the precipitation in

April and November could be predicted effectively by using SSTs. Spatially, there exists a teleconnection relationship between SSTs and the precipitation. The contribution of SSTs to the precipitation in northwest China was greater than that in east China.

Based on the data of monthly mean 500 hPa height fields and the observations from 160 stations in summer from 1951–2002, Yan et al. (2006) investigated the relationship between summer rain patterns over east China and the northern atmospheric circulation from January to May by using the composite analysis and the variance of multi-variable factors. It was found that there is a significant correlation between the spatial and temporal evolution of the atmospheric circulation at 500 hPa from January to February and the distribution of rain patterns in the rainy season over China. However, because spring is the transition season, this kind of correlation is generally not obvious during spring. Even though the distribution of rain patterns in the rainy season responds to different atmospheric circulation fields in previous seasons, there are still only three key areas which pass the significance test in the previous periods, especially in January and February. Yan et al. (2006) further indicated that the longitude range of the westerly index in the key areas is consistent with that of the height anomaly field. The 1st and 2nd key areas are located between 150°–170°E (in front of the East Asian trough) and 100°–80°W (behind the North American trough) in January and February. The 3rd key area lies between 80°–45°W over the Atlantic Ocean in February. In the significant key areas, the higher (lower) westerly index is usually corresponding to the negative (positive) anomalies of the height field from January to February. If there is a higher westerly index around the area of the Atlantic Ocean (80°–45°W) and the anomaly of the height field in the 3rd key area is consistent with the mean of the 500 hPa geopotential height, especially in February, the 1st rain pattern will appear in the upcoming summer. If the westerly index is lower and the anomaly of the height field is positive in the 1st key area, and the distribution of the westerly index and the anomaly of the height field are opposite synchronously in the 2nd key area, the 2nd rain pattern will appear in the coming summer, and conversely, the 3rd rain pattern will appear. These show that there is a close relationship between the westerly index and the rain patterns in the rainy season over China, too. Therefore, it is valuable to analyze the influence of the mid- and high- latitude atmosphere circulation during winter for finding some new prediction clues of the summer precipitation over China.

4. Predictability in ensemble and downscaling forecasts

4.1 *Ensemble forecasts*

4.1.1 *Convective instability in the atmosphere*

Focusing on the convective instability in the atmosphere, Chen et al. (2005) designed a new method to generate initial perturbations for ensemble forecasts of mesoscale heavy rain, namely Different Physical Mode Method (DPMM). In Chen et al. (2005), the initial perturbations that reflect the uncertainty of convection instability were generated by DPMM, where the differences between the predictions with the different Cumulus Convective Parameterization (CCP) schemes were used. The methodology and mathematical scheme of the DPMM demonstrated by Chen et al. (2005) are as follows. First, the differences of moisture flux divergence at 500 hPa from the 12-h prediction are employed to generate the normalized initial perturbation mode; second, the observation errors of the atmosphere are used to determine the perturbation amplitude of zonal wind u, meridional wind v, and temperature T; third, the perturbation of specific humidity q is calculated with T and relative humidity r; finally, by adding the perturbation value and deducting it from the control initial condition, the initial perturbations can then be generated. Using the DPMM method, Chen et al. (2005) performed an ensemble forecast experiment with respect to a heavy rain case occurring in Guangdong and Fujian Provinces on 8 June 1998 within the non-hydrostatic version of the Pennsylvanian State University/National Center for Atmospheric Research Fifth Generation Mesoscale Model (MM5). The results showed that the DPMM normalized initial perturbation mode is not evenly distributed with a reasonable mesoscale circulation structure. The horizontal structure and scale are similar to those of the atmospheric gravity wave mode. The area of maximum perturbation amplitude appears in the warm and humid air belt associated with the southwest low-level jet on the west side of the western Pacific subtropical high, where the heavy rain mainly occurs according to the previous studies. Different initial perturbations can trigger different convective activity with apparent differences of location and strength of precipitation among ensemble members. The ensemble outputs of 24-h accumulated precipitation, including the ensemble mean, the probability exceeding 50 mm, and the spread, showed that the ensemble predictions can obviously improve the controlling prediction by the DPMM initial perturbation methods. The structures of the normalized initial perturbations and the ensemble outputs demonstrated that the DPMM can find the convection-sensitive area and reflect the prediction uncertainty in the sensitive regions of convection instability.

4.1.2 *Typhoons*

The application of ensemble forecast to the problem of tropical cyclone (TC) motion and intensity predictions is still in its infancy, and more researches are necessary to establish the viability of the ensemble forecast technique as an alternative to the traditional deterministic solution in such predictions (Chan, 2002). There were only a few studies for this scenario. A fundamental issue in ensemble forecasts is what method can be used to generate the initial perturbations. Although the breeding of growing modes (BGM) has been tested in TC forecasts by Cheung (2001), its effectiveness remains to be determined, especially when compared with other dynamic techniques such as the lagged-averaged forecast (LAF). Considering this point, Zhou and Chen (2006) investigated the effectiveness of these two different ensemble forecast techniques in the predictability of tropical cyclones by using a baroclinic model. In the BGM experiments, the vortex and the environment were perturbed separately. TC motions in two difficult situations were studied: a large vortex interacting with its environment, and an apparent binary interaction between two TCs. The former is Typhoon Yancy and the latter involves Typhoon Ed and super Typhoon Flo, all occurring during the Tropical Cyclone Motion Experiment, TCM-90. The adopted model was the baroclinic model of the University of New South Wales. The lateral boundary tendencies were computed from atmospheric analysis data. Only the relative skill of the ensemble forecast mean averaged over the control run was used to evaluate the effectiveness of the ensemble methods, although the ensemble technique was also used to quantify forecast uncertainty in some studies. In the case of Yancy, the ensemble mean forecasts of each of the three methodologies were better than that of the control run, with the LAF being the best. The mean track of the LAF was close to the best track, and it predicted landfall over Taiwan. The improvements in the LAF and the full BGM suggested the importance of combining the perturbation of the vortex and environment when the interaction between the two was appreciable. In the binary interaction case of Ed and Flo, the forecasts of Ed appeared to be insensitive to perturbations of the environment and/or the vortex, which apparently resulted from erroneous forecasts by the model of the interaction between the subtropical ridge and Ed, as well as from the interaction between the two typhoons, thus reducing the effectiveness of the ensemble technique. Nevertheless, the forecast tracks in some cases were improved. On the other hand, the ensemble technique had little impact on the forecasts of Flo because the control forecast was already very close to the best track. Zhou and Chen (2006) suggested that their results may provide a basis for the future development of the ensemble technique.

4.2 *Downscaling forecasts*

By downscaling, the small-scale weather processes such as those that influence precipitation and air temperature can be predicted through large-scale weather systems having high predictability. Two approaches are generally used to perform the downscaling forecast: dynamical and statistical downscaling. Dynamical downscaling has definite physical meaning. Although the statistical downscaling has ambiguous physics, it can be conveniently used (Li and Chen, 1999). Considering the advantages of both approaches, Li and Chen (1999) presented a blending method of dynamical and statistical methods, which established a relationship between monthly precipitation anomalies and the monthly circulation. Based on this relationship, Chen et al. (2003b) further developed a new downscaling model which combines the dynamical and statistical downscaling to the precipitation forecast. Statistical weights of each item in the relationship (the downscaling model) were derived from the monthly NCEP/NCAR reanalysis data (500 hPa) and China's observed precipitation data during the control period from January 1951 to December 1991. Then a hindcast test was performed by using the data from January 1992 to December 2001. The new downscaling model has a high skill score for the monthly mean precipitation forecasts. By using the 500 hPa height forecast obtained from the T63/NCC GCM from January to June 2002, Chen et al. (2003b) compared the monthly forecast of precipitation amounts between the issued operational forecast and that from the downscaling model. The results demonstrated that the downscaling model has a higher forecast score than the issued operational forecast.

5. Summary and discussion

In this paper, we reviewed the progresses in predictability studies achieved by Chinese scientists during 2003–2006. The work consists of two parts: theoretical and applied studies. In the theoretical studies, Chinese researchers proposed two novel concepts of CNOP and NLLE, then used them to address the effects of nonlinearity on weather and climate predictability. In the applied studies, they studied the phenomenon of SPB for ENSO and presented a possible mechanism of SPB. Additionally, to improve the predictability of some forecast models, new approaches were developed, which include the design of a new initialization scheme of an intermediate coupled model, the use of the real-time initial atmospheric data in the IAP9L-AGCM, and the use of the reconstruction phase space theory and the spatio-temporal series predictive method in a nonlinear dynamical regional prediction model. The relationships between SSTs and the precipitation in China, and between the summer precipitation patterns and the atmospheric circulation, were also explored using the historical observational data. In ensemble forecast studies, a new initial perturbation method was used for mesoscale heavy rain forecasts and its applicability was shown for the hindcast of the heavy rain case of Guangdong and Fujian Provinces on 8 June 1998. Furthermore, the ensemble forecast approach was adopted to investigate the predictability of tropical typhoons. In downsacling forecasts, considering the respective weaknesses of dynamical and statistical downscaling, Chinese scientists developed a new downscaling model, which is a mixture of dynamical and statistical methods. This new downscaling model can be conveniently used. In hindcast experiments, it showed a higher skill score than the issued operational forecast.

Atmospheric and oceanic motions are very complex. The corresponding numerical models are only a very rough approximation to them, and do not sufficiently consider their "history", and there is a lack of pertinency of the forecast objective. The predictability of weather and climate is therefore limited. Wang (1993) pointed out that although these essential limitations exist, we should not think that we do not need to develop the numerical models. In contrast, we do not only need to develop the models, but also consider the applications of the theoretical results in models. In the studies of predictability theories, it is important to understand the dynamics of uncertainties. Tennekes (1992) proclaimed that no forecast was complete without an estimate of the forecast error. The forecast errors can be caused by initial errors and model errors. In the "perfect model scenario", it is assumed that the predictability is limited only by the growth of initial uncertainties. However, practical predictability experiments are often carried out with an imperfect model forecasting observational data. Model error exists in the particular model employed. The predictability quantified by numerical models may under- or overestimate the inherent predictability. That is to say, the different models may show different predictability due to model errors.

During the period of 2003–2006, Chinese scientists conducted many theoretical studies on initial uncertainties with the assumption of perfect models. It is anticipated that the effect of model error on predictability will be involved in future studies. It is hoped that the combination of theoretical studies and practical applications can lead to the improvement of forecast skill.

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