SCIENCE CHINA
Earth Sciences

•ARTICLE•

https://doi.org/10.1007/s11430-022-1094-0

A multi-model prediction system for ENSO

Ting LIU[1,2], Yanqiu GAO[1,2], Xunshu SONG[1,2], Chuan GAO[3,9], Lingjiang TAO[4], Youmin TANG[5,6*], Wansuo DUAN[7], Rong-Hua ZHANG[8,9] & Dake CHEN[1,2†]

[1] *State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, Ministry of Natural Resources, Hangzhou 300012, China;*
[2] *Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai), Zhuhai 519000, China;*
[3] *Key Laboratory of Ocean Circulation and Waves, Institute of Oceanology, and Center for Ocean Mega-Science, Chinese Academy of Sciences, Qingdao 266071, China;*
[4] *Department of Atmospheric and Oceanic Sciences and Institute of Atmospheric Sciences, Fudan University, Shanghai 200438, China;*
[5] *College of Oceanography, Hohai University, Nanjing 210098, China;*
[6] *Environmental Science and Engineering, University of Northern British Columbia, Prince George, British Columbia V2N 4Z9, Canada;*
[7] *State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, University of Chinese Academy of Sciences, Beijing 100029, China;*
[8] *School of Marine Sciences, Nanjing University of Information Science and Technology, Nanjing 210044, China;*
[9] *Laoshan Laboratory, Qingdao 266237, China*

Received October 31, 2022; revised March 6, 2023; accepted March 27, 2023; published online May 15, 2023

Abstract The El Niño and Southern Oscillation (ENSO) is the primary source of predictability for seasonal climate prediction. To improve the ENSO prediction skill, we established a multi-model ensemble (MME) prediction system, which consists of 5 dynamical coupled models with various complexities, parameterizations, resolutions, initializations and ensemble strategies, to account for the uncertainties as sufficiently as possible. Our results demonstrated the superiority of the MME over individual models, with dramatically reduced the root mean square error and improved the anomaly correlation skill, which can compete with, or even exceed the skill of the North American Multi-Model Ensemble. In addition, the MME suffered less from the spring predictability barrier and offered more reliable probabilistic prediction. The real-time MME prediction adequately captured the latest successive La Niña events and the secondary cooling trend six months ahead. Our MME prediction has, since April 2022, forecasted the possible occurrence of a third-year La Niña event. Overall, our MME prediction system offers better skill for both deterministic and probabilistic ENSO prediction than all participating models. These improvements are probably due to the complementary contributions of multiple models to provide additive predictive information, as well as the large ensemble size that covers a more reasonable uncertainty distribution.

Keywords MME, ENSO, Prediction

Citation: Liu T, Gao Y, Song X, Gao C, Tao L, Tang Y, Duan W, Zhang R H, Chen D. 2023. A multi-model prediction system for ENSO. Science China Earth Sciences, 66, https://doi.org/10.1007/s11430-022-1094-0

1. Introduction

The El Niño and Southern Oscillation (ENSO) is the most pronounced large scale air-sea coupling phenomenon that originates in the tropical Pacific approximately every 2–7 years. The thermal forcing associated with ENSO on the atmosphere circulation is of central importance for driving global climate variability. Thus, ENSO has been recognized as a primary source for global climate predictability on

* Corresponding author (email: ytang@unbc.ca)
† Corresponding author (email: dchen@sio.org.cn)

seasonal to interannual timescales (McPhaden et al., 2006). The ability to sufficiently predict the warm and cold episodes of upcoming ENSO events in advance is vital for regional short-range climate prediction, which is matters for the effective precautions of climate disasters and mitigation of the potential risk to life and property those disasters may pose. Inspired by the pioneering work of Cane et al. (1986), the prediction of ENSO has made tremendous progress with generations of efforts. The real-time predictions of ENSO are routinely issued in a number of operational climate centers and research groups around the world, with statistical and dynamical models that vary in complexity (Barnston et al., 2012, Tang et al., 2018; Ren et al., 2019). The skillful prediction of ENSO can be made 6–12 months in advance. However, the prediction of ENSO still involves substantial challenge, which is mainly limited by the uncertainties that originate from the initial conditions, the diversity of ENSO states and the imperfect representation of the physical processes of ENSO in models (Tang et al., 2018; Ren et al., 2019). For example, almost all current statistical and dynamical models missed the latest strongest 2015–2016 El Niño event at 12 months in advance. Although the predictions initialized in summer 2015 essentially announced the following evolution of sea surface temperature (SST), the predicted intensity of this event diverged considerably across the models. Therefore, the improvement of ENSO prediction is a timeless focus from both a scientific perspective and social aspect.

One of the effective strategies for tackling the uncertainties related to ENSO prediction is the multi-model ensemble (MME) approach, which combines a suite of predictions with different initial conditions based on various models to better sample future trajectories. Each of these models involves somewhat different resolutions, parameterization schemes, physical processes and initial states, and has individual strengths and weaknesses. The theme of the MME method is to take into account the combined effect from the uncertainties in the initial condition and model formulation. Model diversity can contribute complementary predictive information by cancelling out a portion of the model errors after averaging within the MME method (Hagedorn et al., 2005; Tippett and Barnston, 2008; DelSole et al., 2014). Moreover, the increased ensemble size in MME is beneficial to sample forecast probability distribution and reduce the systematic "misfires" associated with any one particular model, which allows for a better quantification of forecast uncertainty. Therefore, the MME approach has been demonstrated to be superior to a single model ensemble, and more valuable for decision makers to manage risks associated with ENSO events (Wang et al., 2009; Becker et al., 2014; Min et al., 2014). MME seasonal prediction systems have been widely developed at major operational centers and research institutions, such as: the European Centre for Medium-Range Weather Forecasts (ECMWF) (Palmer et al., 2004), the Asia-Pacific Economic Cooperation Climate Center (APCC) (Jeong et al., 2012), the International Research Institute for Climate and Society (IRI) (Barnston et al., 2012) and the National Climate Center (NCC) of the China Meteorological Administration (CMA) (Ren et al., 2019). Since early 2012, the IRI has issued the real-time ENSO prediction plume each month with 17 dynamical models and 7 statistical models (https://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/?enso-sst_table). Recently, the NCC/CMA established the China multi-model ensemble prediction system version 1.0 (CMMEv1.0) to provide monthly real-time MME ENSO prediction with 13 dynamical models, 4 statistical models and 3 hybrid dynamical- statistical models (http://ncclcs.ncc-cma.net/Website/?ChannelID=254). The above two have been critical references for international or national operational ENSO outlooks.

The MME ENSO prediction is tentative in China (Ren et al., 2019). Inspired by those pioneering works, we developed another MME ENSO prediction system with 5 dynamical models ranging from intermediate coupled models (ICMs) to fully coupled general circulation model (CGCM). This MME system involves the implementation of a new model (Song et al., 2018), new ensemble forecast methods (Liu et al., 2019; Liu et al., 2022), new parameter scheme (Zhang and Gao, 2016; Gao et al., 2022) or new data assimilation approach (Duan and Zhou, 2013; Tao and Duan, 2019; Gao et al., 2020; Duan et al., 2022; Song et al., 2022). Moreover, a long-term retrospective forecast over the past 137 years (1881–2017) was conducted to evaluate the ENSO forecast skill and useful forecast data were obtained. Additionally, the real-time monthly prediction has been routinely issued starting in October 2020. In this study, we will introduce the current progress of this MME prediction system and its ENSO forecasts.

2. Model and methodology

2.1 The MME system

This MME system consists of three regional ICMs for tropical Pacific region, one regional ICM for the tropics and one CGCM. M1 is the extension of the Lamont-Doherty Earth Observation (LDEO 5) model (Chen et al., 2004). We have updated its data assimilation process from the nudging scheme to Ensemble Kalman Filter (EnKF) method, and also established an ensemble prediction system based on the stochastic optimal (SO) perturbation approach to sample the uncertainties associated with atmospheric processes (Tang et al., 2018; Liu et al., 2019; Gao et al., 2020). M2 was developed by Zhang et al. (2003), and has been used for routine ENSO prediction and collected in IRI ENSO prediction plume since 2003. After optimizing the model parameters in terms of ENSO simulations and retrospective predictions, this model was used at the Institute of Oceanology, Chinese Academy of Sciences (IOCAS) and named the IOCAS ICM, which has been routinely used to predict the SST evolution in the tropical Pacific with success since August 2015 (Zhang and Gao, 2016; Zhang et al., 2022). To take the combined effect from model errors with various sources into consideration, M3 embedded a model tendency perturbation into M2 to neutralize the prediction errors caused by both the initial and model errors by using a new data assimilation approach of nonlinear forcing singular vector (NFSV-DA) (Duan and Zhou, 2013; Tao and Duan, 2019; Duan et al., 2022). This model can distinguish the two types of El Niño two-season in advance (Tao et al., 2020). M4 promoted the physical framework of the Zebiak-Cane model to the entire global tropics. To improve the model performance and accuracy for SST variability in the entire tropical oceans and the inter-basin connections, some improvements were added to this model, including the surface wind bias correction process and surface heat flux parameterization scheme (Song et al., 2018). M5 is the widely used CGCM, CESM 1.2, which is the operational model in the National Marine Environmental Forecasting Center (NMEFC) of China (Li et al., 2015). We have proposed an improved nudging scheme for the prediction system of NMEFC by increasing the nudging weight at the subsurface and adding wind components assimilation. This new scheme can effectively improve the simulation and prediction performance for ENSO (Song et al., 2022). In addition, a cost-efficient ensemble construction strategy generated from the climatically relevant singular vector method is introduced to establish an ensemble prediction system for M5, which significantly improves the prediction performance compared with the single prediction (Liu et al., 2022). More detailed information on each model is summarized in Table 1. In brief, this MME system includes diverse models that vary in their complexity levels, horizontal and vertical resolutions, physical parameterizations, data assimilation processes, initialized datasets and ensemble construction strategies, which accounts for the uncertainties as comprehensively as possible.

The individual model retrospective forecast was initiated on January 1st, April 1st, July 1st and October 1st each calendar year from 1881 to 2017, with a lead up to 12 months. To remove the mean bias of each model, the individual model anomalies are derived by subtracting its own hindcast seasonal climatology. In this study, we employed the commonly used "equal weight" approach to construct MME by assigning the same weight to each model. Compared with the models that only provide a single hindcast, the M1 and M5 have their own ensemble outputs. Therefore, the corresponding ensemble mean is employed to form the MME.

2.2 Methodology

To evaluate the deterministic prediction skill, we employ the anomaly correlation coefficient (ACC) and the root mean square error (RMSE), which are defined as:

$$ACC(t) = \frac{\sum_{i=1}^{N}\left[x_i^f(t)-\overline{x^f}(t)\right]\left[x_i^o(t)-\overline{x^o}(t)\right]}{\sqrt{\sum_{i=1}^{N}\left[x_i^f(t)-\overline{x^f}(t)\right]^2}\sqrt{\sum_{i=1}^{N}\left[x_i^o(t)-\overline{x^o}(t)\right]^2}}, \tag{1}$$

$$RMSE(t) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_i^f(t)-\overline{x^f}(t)\right)^2}, \tag{2}$$

where $x_i^f(t)$ and $x_i^o(t)$ are the MME mean prediction and the corresponding observation of interest variable for the i th initial condition at the tth lead month, respectively. $\overline{x^f}$ and $\overline{x^o}$ denote the model climatology and observational climatology, respectively. N indicates the total number of hindcasts (137 years × 4 months=548).

We also employ the Brier skill score (BSS; Wilks, 2011) to

Table 1 Information of the participating models in MME prediction system [a)]

Model	Complexity	Region	Data assimilate	Ensemble strategies
M1	Intermediate complexity	Tropical pacific ocean	EnKF A: ERA-20C UV O: Kaplan SST	EnKF+SOs
M2	Intermediate complexity	Tropical pacific ocean	Linear interpolation O: Kaplan SST	/
M3	Intermediate complexity	Tropical pacific ocean	Nudging O: ERSST V5	/
M4	Intermediate complexity	Tropic	Nudging O: Kaplan SST	/
M5	CGCM	Global	Nudging A: ERA-20C + ERA-Interim UV O: SODA+GODAS sea temperature	CSVs

a) A: Atmosphere; O: Ocean; SO: Stochastic optimal (Kleeman and Moore, 1997); CSV: Climatically relevant singular vector (Kleeman et al., 2003) measure the probabilistic skill. The BSS assesses the Brier score (BS) relative to the reference climatological forecast, which measures the mean squared error between the forecast probability and observed frequency as:

$$BS = \frac{1}{N}\sum_{m=1}^{M} n_m(\bar{x}_m - \bar{o}_m)^2 - \frac{1}{N}\sum_{m=1}^{M} n_m(\bar{o}_m - \bar{o})^2 + \bar{o}(1-\bar{o}), \tag{3}$$

$$BSS = 1 - \frac{BS}{BS_{CLM}}, \tag{4}$$

where x and o are the forecast probability and corresponding observed frequency of an event, respectively. The terms $\bar{x}_m$ and $\bar{o}_m$ are the mean of all x and the relevant observed outcomes falling in the mth bin, and n_m is the number of predictions occurring in this bin. N denotes the total number of predictions (initial conditions). M is the number of probabilistic bins from 0.1 to 1.0 by 0.1 intervals. $\bar{o}$ is the observed climatological probability represented by the mean of $\bar{o}_m$.

As $BS_{CLM} = \bar{o}(1-\bar{o})$, BSS indicates the improvement of the probabilistic forecast relative to the climatological forecast. A positive value of BSS means skillful probabilistic forecast, whereas a negative value indicates that the forecast is inferior to the climatological forecast.

We employ the Niño3.4 index to represent the ENSO variation , which is defined by the averaged SST anomalies in the central and eastern Pacific Ocean (5°S–5°N, 170°E–120°W). Following previous studies (Yang et al., 2016, 2018; Liu et al., 2019; Yang et al., 2021), we split each category into terciles to ensure that the three types of events have an equal climatological frequency of 1/3. The below normal events (lower 1/3 tercile), neutral events (middle 1/3 tercile), and above normal events (upper 1/3 tercile) are defined by the climatic probability density distributions of the observed Niño 3.4 indexes from 1881 to 2017. For the model reforecasts, the "one-month-lead forecast" means the monthly forecast initiated in the first day of the current month itself. For example, the monthly mean forecast of the January is defined as one-month-lead for the forecast initiated from 1st January. The validation data for the SST were extracted from the Kaplan SST version 2 datasets (Kaplan et al., 1998), which is the commonly assimilated SST data for participating models in MME prediction system.

3. Performance of ENSO in the MME

3.1 Improvement of deterministic prediction in the MME

The predicted ensemble means of the Niño3.4 index (blue line) and the corresponding observations (red line) are presented in Figure 1. The MME prediction generally predicted most ENSO events over the past 137 years ahead of one year, especially for prominent warm and cold events. At 6-month lead time, the hindcasts are consistent with the observations quite well, with an ACC of 0.83. By 12-month lead time, there is a certain degradation in the agreement between the observations and the hindcasts, with an ACC of 0.59. The observed El Niño and La Niña events can also be relatively well reflected, but there is a tendency to underestimate their amplitudes with respect to the observations as the lead time increases. Figure 2 presents the ACC and RMSE between the predicted Niño3.4 index in the MME (red line) and individual models (colord lines) and the corresponding observations. In general, the ACC and the RMSE of the MME prediction exhibit substantial superiority to its contributing models for all lead times, and high prediction skill corresponds to large ACC and small RMSE values. MME prediction can generate skillful forecasts (ACC>0.5) 12 months in advance. During the common period (1982–2010), which covers most current ENSO hindcasts of CGCMs in the North American Multi-model Ensemble (NAMM, Kirtman et al., 2014), the MME prediction still provides higher ACC and RMSE skill with respect to all participating models (Figure 3). The ACC skills of the MME predictions are 0.95, 0.87 and 0.76 at 3, 6, and 9 month leads, respectively. This outperforms, or is at least comparable with, the performance of the MME of NAMM, which has ACCs are 0.91, 0.83 and 0.7 at 3, 6, and 9 month leads, respectively (Barnston et al., 2019). In brief, the performance of our MME prediction supports the superiority of the multimodel approach, which has a beneficial impact on cancelling model errors contained in individual models and highlighting complementary nature of the models' contributions. Our MME system performs competitively with, or even exceeds the NAMM in terms of ENSO prediction. This encouraging result boosts us confidence in applying this MME system to real-time ENSO predications.

3.2 Improvement of the spring predictability barrier (SPB) in the MME

As is commonly acknowledged, there is a pronounced seasonal variation in ENSO prediction skill, which is referred to as SPB (Webster and Yang, 1992). The SPB feature is common to all participating models within MME system to varying degrees (Figure 4). The prediction skills exhibit a marked decline when the forecasts traversing the boreal spring. The forecasts initiated in July and October tend to have a slower decline in skill than the cases that starred in January and April. Even so, the MME predictions verify better than other models when compared against observations and features a relatively gentle decline of ACC across the northern spring. The lead months for the effective predictions (ACC>0.5) are significantly longer in the MME

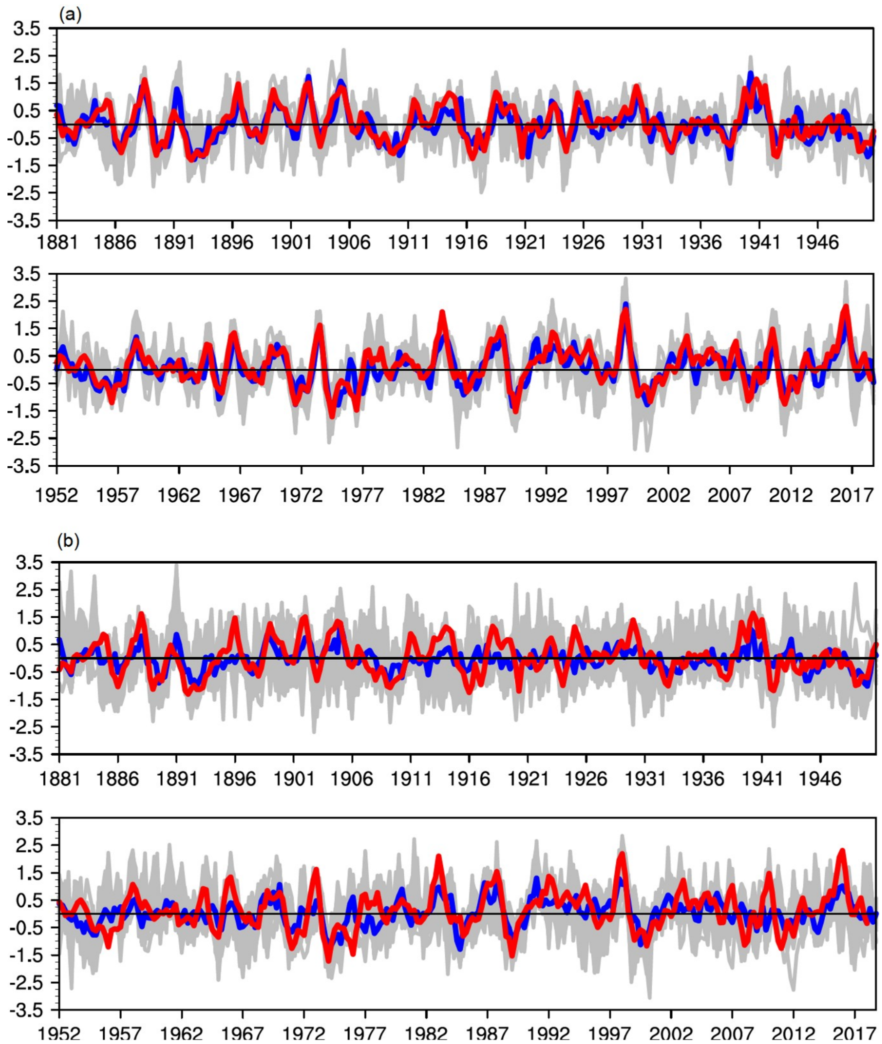

Figure 1 Time series of the MME forecasted Niño 3.4 index at a six month lead (a) and twelve month lead (b) against the corresponding observations. The red and blue lines are the observations and ensemble mean, respectively. The gray shading represents the prediction spread.

prediction than all participating models. This indicates that, unlike any individual model, the MME prediction is only weakly impacted by SPB, which is owing to the MME algorithm is a useful tool for the reduction of the model errors contained in individual models, and also contributes additional forecast signals (Palmer et al., 2004; Hagedorn et al., 2005; DelSole et al., 2014). Therefore, MME is also a potential tool to improve model performance in terms of alleviating SPB.

3.3 Improvement of probability prediction in MME

In this MME system, the hindcasts of M1 and M5 are generated by their own ensemble system, with 100 and 20 members, respectively Hence, we can also evaluate the performance of the MME (with 123 members) in probabilistic predictions compared with the single model ensembles. Figure 5 presents the BSS of the MME (red line), M1 (green line) and M5 (blue line) predictions. The full MME forecasts systematically improve the BSS of the participating models at every lead times for all three categories of ENSO events. The skillful probabilistic skill (BSS>0) of the MME is 11 months ahead of neutral events, which is a substantial improvement compared with the performance of individual model ensembles. The superior performance of the MME prediction is essential in terms of both the resolution (Figure 6) and reliability (Figure 7), and the major contribution is due to the decreased reliability component. These two components give insight into different aspects of forecast performance. The reliability indicates the difference between a forecast probability for an event and the observed frequency of that event. The resolution measures the ability of the forecast system to assign probabilities different from the climatological probability. The above improvements may be due to the enlarged ensemble size offered by the MME method can express a more reasonable sampling of forecast uncertainties, which contains the observation more often and provides a more reliable probabilistic prediction. We have

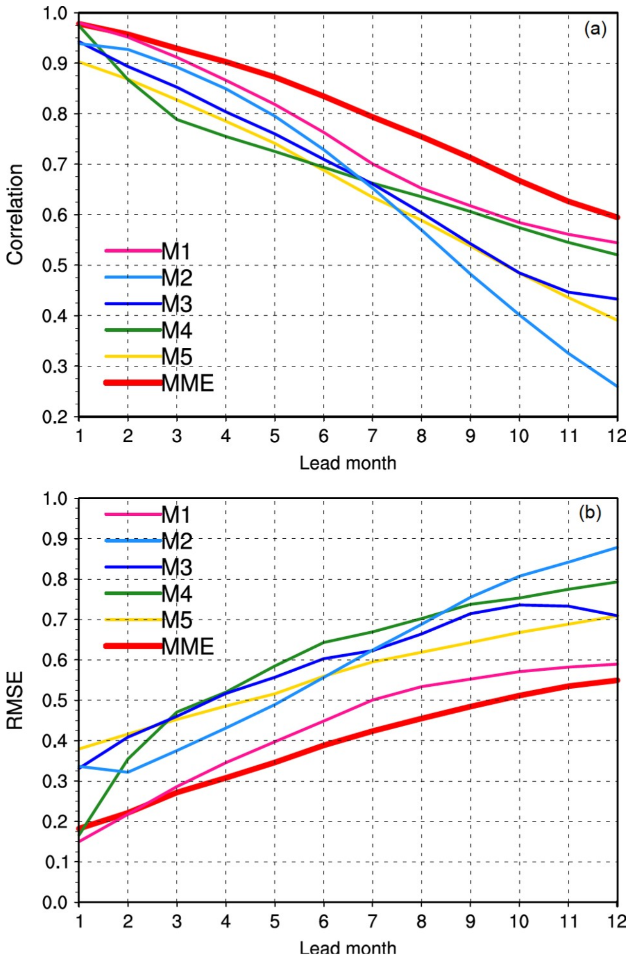

Figure 2 ACC (a) and RMSE (b) of the forecasted Niño 3.4 indexes compared with the observations from 1881 to 2017. The red and other colored lines indicate the MME prediction and the individual models, respectively.

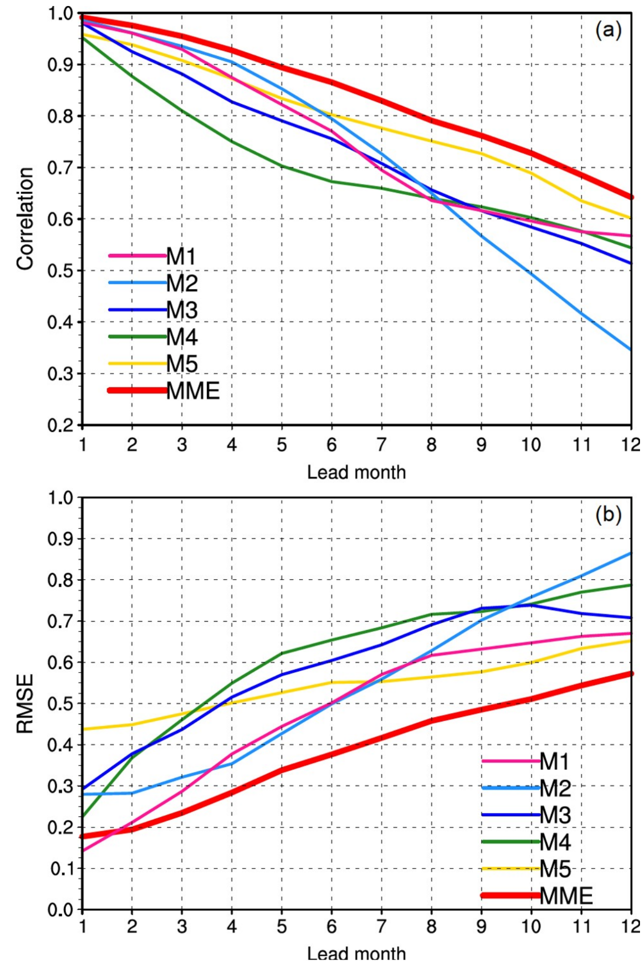

Figure 3 ACC (a) and RMSE (b) of the forecasted Niño 3.4 indexes compared with the observations from 1982 to 2010. The red and other colored lines indicate the MME prediction and the individual models, respectively.

also checked the relative operating characteristic (ROC; Mason and Graham 1999) skill, which is another widely used probabilistic measure (Dewitt, 2005; Chen and Cane, 2008; Zheng et al., 2009) and essentially reacting the similar characteristics of resolution term of BSS (Yang et al., 2021). Compared with any one particular model, the MME also exhibits the highest ROC skill at each lead times for all three categories of ENSO events (not shown). This further indicates that the skillful MME probabilistic prediction will exert additional potential economic value than the single model ensembles.

3.4 Performance of the real-time prediction in MME

Based on our MME system, routine real-time ENSO predictions are issued each month from October 2020, which can be found at https://soed.sio.org.cn/emsodm.html. The real-time predictions generally predicted the evolution of the observed SST in the tropical central and eastern Pacific Ocean during the last year or more. The latest two successive La Niña events were adequately depicted by the MME predictions (Figure 8). The secondary cooling trend was reasonably captured when the prediction was initiated in June 2021. The MME prediction system has forecast the emergence of an upcoming three-year cooling since it was initiated in April 2022, which would be the first three-year La Niña event since 2001. Our MME predictions were also well consistent with the IRI MME prediction plume over the past year or more. However, it should be noted that some uncertainties remain due to the influence of the SPB. Compared to the observations, the predictions targeted across the spring verify were worse than predictions from other times of the year. Even so, the MME prediction performs better than any participating models across spring.

4. Conclusion and discussion

The large amplitude SST variability associated with warm and cold ENSO episodes can exert persistent thermal forcing

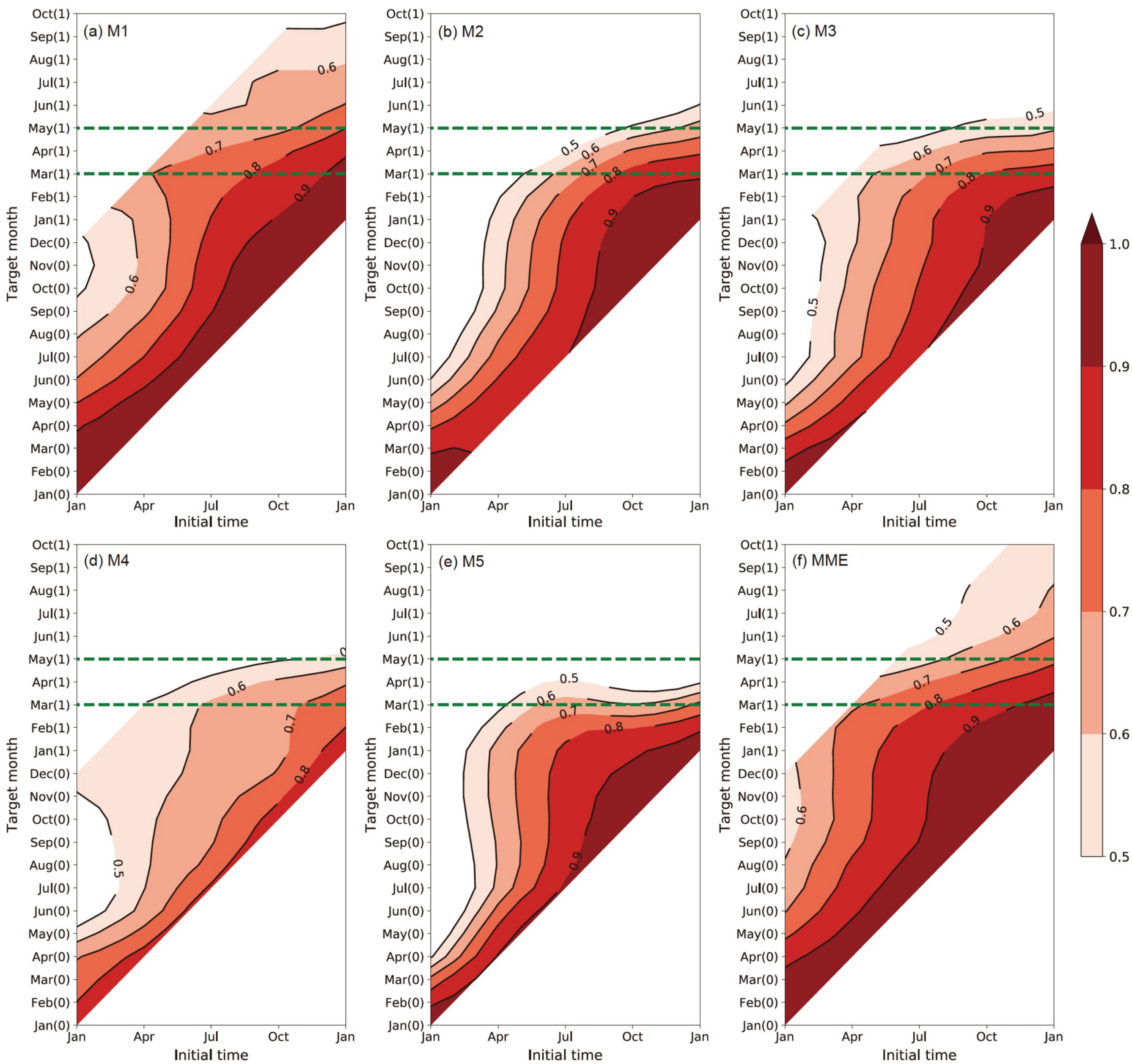

Figure 4 ACC of the forecasted Niño 3.4 index compared with the observations for different start months of individual models ((a)–(e)) and MME (f).

on atmospheric circulation, which provides the primary scientific basis for seasonal predictions. Therefore, the ability to accurately represent and predict ENSO behavior is of particular interest. A successful prediction for the upcoming ENSO event has foreseeable enormous economic and social value in grappling with climate disasters. There are several potential sources of uncertainties arising from the initial conditions, model configuration or chaotic behavior of the air-sea coupled dynamic system accounting for the loss of ENSO predictability. The MME approach is an effective tool to improve forecast quality for ENSO prediction (Barnston et al., 2012; Kirtman et al., 2014; Barnston et al., 2019). The collection of multiple models allows for a better sampling of the probability distribution and forecast uncertainties, which has the potential to combine the benefits relative to all participating members, reduce errors and quantify forecast uncertainties. This study introduces a recently developed MME prediction system for ENSO, which uses multiple-model configurations of up to five coupled dynamic models for various representations of physical processes, numerical schemes, resolutions, ensemble construction strategies and the use of observations to construct initial conditions with different data assimilation methods. This combination of ensembles from different models aims to take into consideration uncertainties arising from various sources as comprehensively as possible. Long-term retro-

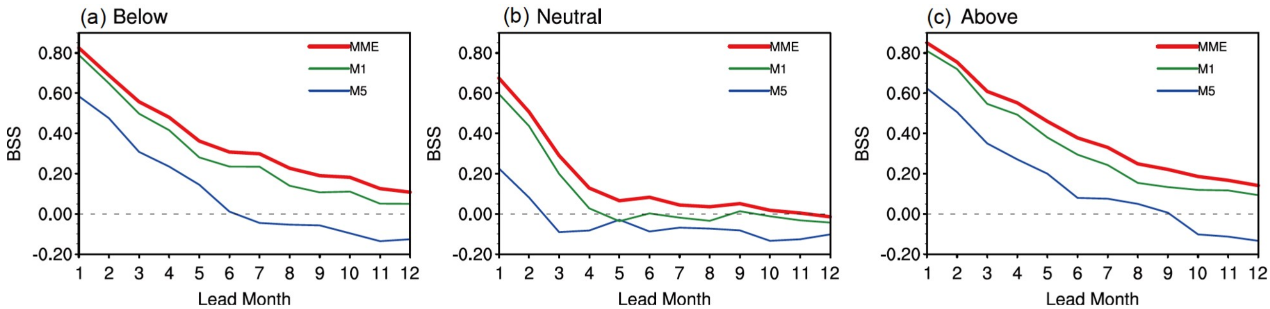

Figure 5 BSS of the MME forecasted (red line) and individual model ensemble Niño 3.4 indexes (blue and green lines) for below normal (a), neutral (b) and above normal events (c) as a function of lead time from 1881 to 2017.

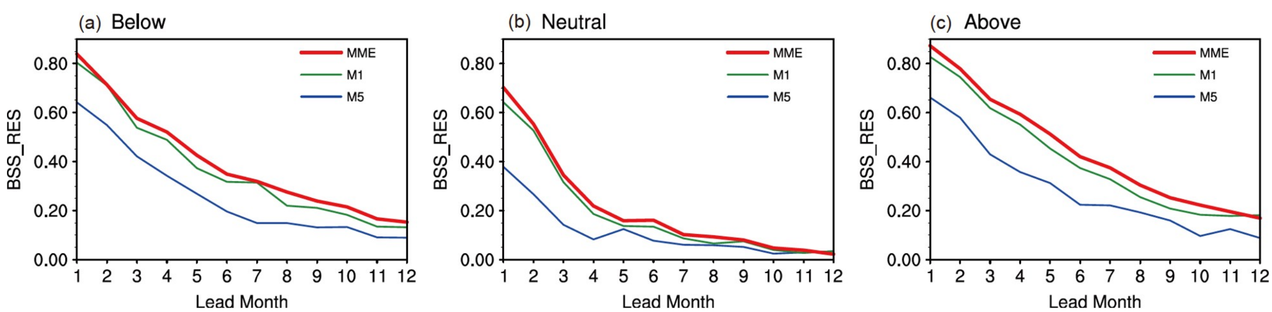

Figure 6 The resolution component of the MME forecasted (red line) and individual model ensemble Niño 3.4 indexes (blue and green lines) for below normal (a), neutral (b) and above normal events (c) as a function of lead time from 1881 to 2017.

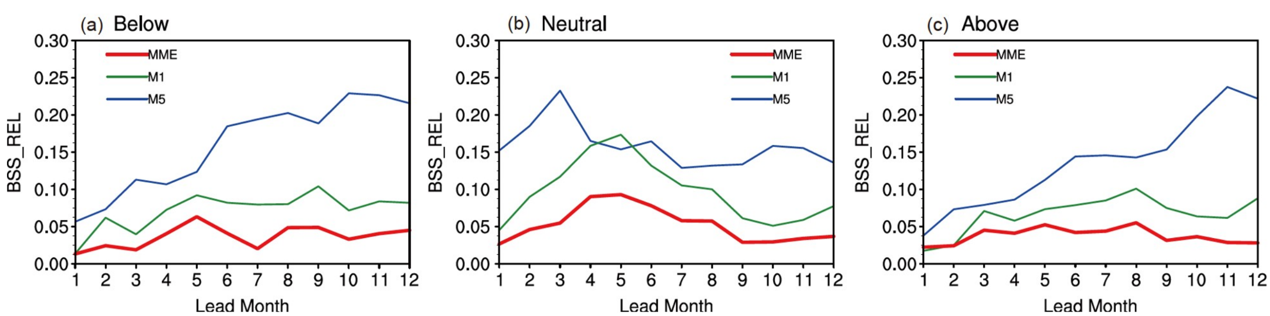

Figure 7 The reliability component t of the MME forecasted (red line) and individual model ensemble Niño 3.4 indexes (blue and green lines) for below normal (a), neutral (b) and above normal events (c) as a function of lead time from 1881 to 2017.

spective forecast has been conducted and verified from both deterministic and probabilistic perspectives. Our results, as expected, provide evidence of the superiority offered by the MME predictions:

(1) MME predictions appear to drastically improve the ACC skill and reduce the RMSE with respect to all participating models. Our MME prediction skill can compete with, or even exceed the NAMM in terms of ENSO prediction.

(2) Compared with the individual models, the MME prediction performance was better in the SPB, with a relatively gentle decrease in ACC during the boreal spring and significantly longer effective prediction lead time.

(3) MME prediction can offer a more reliable probabilistic prediction, with considerable improvement in the reliability and resolution components, especially for the reliability term.

(4) The MME prediction adequately declared the latest two successive La Niña events and reasonably captured the secondary cooling trend six months in advance. It has also predicted the coming of a third-year cooling since April 2022.

Overall, our MME ENSO prediction outperforms all participating models and issues more skillful deterministic and probabilistic predictions. These marked improvements are due either to the complementary nature of multiple models' contributions to provide additive predictive information or a larger ensemble size expressing a more reliable distribution of uncertainties. Therefore, the MME approach is an effective and pragmatic strategy for operational ENSO prediction, which can offer potential economic and scientific value to

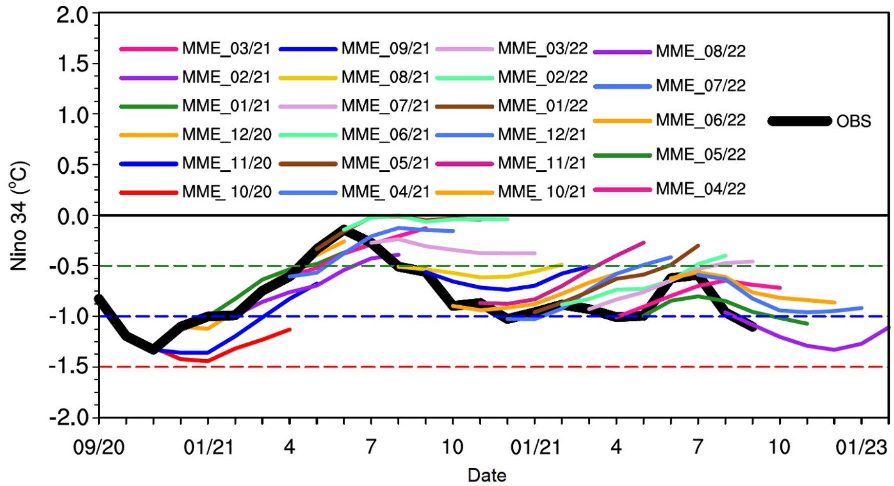

Figure 8 The real-time MME forecasted Niño 3.4 indexes during the past months. The black and other colored lines indicate the observations and the MME prediction initiated since October 2020, respectively.

decision makers and end users. However, this MME prediction system is still in its initial stage, and many efforts should be devoted to its further improvement. Two possible options will be taken into consideration to reduce the forecast errors. On the one hand, advanced empirical postprocessing techniques will be introduced to correct the prediction errors. On the other hand, sophisticated linear or nonlinear combination schemes based on super-ensemble idea (Krishnamurti et al., 1999, 2016) will be employed to assign optimal and objective weights to participating models according to their historical performance. The MME prediction of ENSO is a nascent but urgent issue in China. By pursuing unremitting efforts, we anticipate that our MME prediction system can issue timely and accurate ENSO predictions and sufficiently satisfy the demands of operational climate prediction and meet the needs of disaster prevention and mitigation.

Acknowledgements *This work was supported by the Scientific Research Fund of the Second Institute of Oceanography, MNR (Grant No. QNYC2101), the Scientific Research Fund of the Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai) (Grant No. SML2021SP310), the National Natural Science Foundation of China (Grant Nos. 41690124 & 41690120), the National Key Research and Development Program (Grant No. 2017YFA0604202) and the Innovation Group Project of Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai) (Grant No. 311021001). Pro. Zhang was supported by the National Natural Science Foundation of China (Grant No. 42030410), the Laoshan Laboratory Programe (Grant No. LSL202202402) and the Startup Foundation for Introducing Talent of NUIST.*

References

Becker E, den Dool H, Zhang Q. 2014. Predictability and forecast skill in NMME. J Clim, 27: 5891–5906

Barnston A G, Tippett M K, L'Heureux M L, Li S, DeWitt D G. 2012. Skill of real-time seasonal ENSO model predictions during 2002–2011: Is our capability increasing? Bull Am Meteorol Soc, 93: 631–651

Barnston A G, Tippett M K, Ranganathan M, L'Heureux M L. 2019. Deterministic skill of ENSO predictions from the North American Multimodel Ensemble. Clim Dyn, 53: 7215–7234

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

Chen D, Cane M A, Kaplan A, Zebiak S E, Huang D. 2004. Predictability of El Niño over the past 148 years. Nature, 428: 733–736

Chen D, Cane M A. 2008. El Niño prediction and predictability. J Comput Phys, 227: 3625–3640

DelSole T, Nattala J, Tippett M K. 2014. Skill improvement from increased ensemble size and model diversity. Geophys Res Lett, 41: 7331–7342

Dewitt D G. 2005. Retrospective forecasts of interan nual sea surface temperature anomalies from 1982 to present using a directly coupled atmosphere-ocean general circulation model. Mon Weather Rev, 133: 2972–2995

Duan W, Zhou F. 2013. Non-linear forcing singular vector of a two-dimensional quasi-geostrophic model. Tellus A, 65: 18452

Duan W, Feng R, Yang L, Jiang L. 2022. A new approach to data assimilation for numerical weather forecasting and climate prediction. J Appl Anal Comput, 12: 1007–1021

Gao Y, Liu T, Song X, Shen Z, Tang Y, Chen D. 2020. An extension of LDEO5 model for ENSO ensemble predictions. Clim Dyn, 55: 2979–2991

Gao C, Chen M, Zhou L, Feng L, Zhang R H. 2022. The 2020–2021 prolonged La Niña evolution in the tropical Pacific. Sci China Earth Sci, 65: 2248–2266

Hagedorn R, Doblas-reyes F J, Palmer T N. 2005. The rationale behind the success of multi-model ensembles in seasonal forecasting—I. Basic concept. Tellus A, 57: 219–233

Jeong H I, Lee D Y, Ashok K, Ahn J B, Lee J Y, Luo J J, Schemm J K E, Hendon H H, Braganza K, Ham Y G. 2012. Assessment of the APCC coupled MME suite in predicting the distinctive climate impacts of two flavors of ENSO during boreal winter. Clim Dyn, 39: 475–493

Kaplan A, Cane M A, Kushnir Y, Clement A C, Blumenthal M B, Rajagopalan B. 1998. Analyses of global sea surface temperature 1856–1991. J Geophys Res, 103: 18567–18589

Kirtman B P, Min D, Infanti J M, Kinter James L. I, Paolino D A, Zhang Q, van den Dool H, Saha S, Mendez M P, Becker E, Peng P, Tripp P, Huang J, DeWitt D G, Tippett M K, Barnston A G, Li S, Rosati A, Schubert S D, Rienecker M, Suarez M, Li Z E, Marshak J, Lim Y K, Tribbia J, Pegion K, Merryfield W J, Denis B, Wood E F. 2014. The North American multimodel ensemble: Phase-1 seasonal-to-interannual prediction; Phase-2 toward developing intraseasonal prediction. Bull Amer Meteor Soc, 95: 585–601

Kleeman R, Moore A M. 1997. A theory for the limitation of ENSO predictability due to stochastic atmospheric transients. J Atmos Sci, 54: 753–767
Kleeman R, Tang Y, Moore A M. 2003. The calculation of climatically relevant singular vectors in the presence of weather noise. J Atmos Sci, 60: 2856–2868
Krishnamurti T N, Kishtawal C M, LaRow T E, Bachiochi D R, Zhang Z, Williford C E, Gadgil S, Surendran S. 1999. Improved weather and seasonal climate forecasts from multimodel superensemble. Science, 285: 1548–1550
Krishnamurti T N, Kumar V, Simon A, Bhardwaj A, Ghosh T, Ross R. 2016. A review of multimodel superensemble forecasting for weather, seasonal climate, and hurricanes. Rev Geophys, 54: 336–377
Li Y, Cai X, Tan J, Huang Y, Cai Y. 2015. An ENSO hindcast experiment using CESM (in Chinese). Acta Oceanol Sin, 37: 39–50
Liu T, Tang Y, Yang D, Cheng Y, Song X, Hou Z, Shen Z, Gao Y, Wu Y, Li X, Zhang B. 2019. The relationship among probabilistic, deterministic and potential skills in predicting the ENSO for the past 161 years. Clim Dyn, 53: 6947–6960
Liu T, Song X, Tang Y, Shen Z, Tan X. 2022. ENSO predictability over the past 137 years based on a CESM ensemble prediction system. J Clim, 35: 763–777
Mason S J, Graham N E. 1999. Conditional probabilities, relative operating characteristics, and relative operating levels. Weather Forecast, 14: 713–725
McPhaden M J, Zebiak S E, Glantz M H. 2006. ENSO as an integrating concept in Earth science. Science, 314: 1740–1745
Min Y M, Kryjov V N, Oh S M. 2014. Assessment of APCC multimodel ensemble prediction in seasonal climate forecasting: Retrospective (1983–2003) and real-time forecasts (2008–2013). J Geophys Res-Atmos, 119: 12,132–12,150
Palmer T N, Alessandri A, Andersen U, Cantelaube P, Davey M, Délécluse P, Déqué M, Díez E, Doblas-Reyes F J, Feddersen H, Graham R, Gualdi S, Guérémy J F, Hagedorn R, Hoshen M, Keenlyside N, Latif M, Lazar A, Maisonnave E, Marletto V, Morse A P, Orfila B, Rogel P, Terres J M, Thomson M C. 2004. Development of a European multimodel ensemble system for seasonal-to-interannual prediction (Demeter). Bull Am Meteorol Soc, 85: 853–872
Ren H L, Wu Y, Bao Q, Ma J, Liu C, Wan J, Li Q, Wu X, Liu Y, Tian B, Fu J X, Sun J. 2019. The China multi-model ensemble prediction system and its application to flood-season prediction in 2018. J Meteorol Res, 33: 540–552
Song X, Chen D, Tang Y, Liu T. 2018. An intermediate coupled model for the tropical ocean-atmosphere system. Sci China Earth Sci, 61: 1859–1874
Song X, Li X, Zhang S, Li Y, Chen X, Tang Y, Chen D. 2022. A new nudging scheme for the current operational climate prediction system of the National Marine Environmental Forecasting Center of China. Acta Oceanol Sin, 41: 51–64
Tang Y, Zhang R H, Liu T, Duan W, Yang D, Zheng F, Ren H, Lian T, Gao C, Chen D, Mu M. 2018. Progress in ENSO prediction and predictability study. Natl Sci Rev, 5: 826–839
Tao L J, Duan W S. 2019. Using a nonlinear forcing singular vector approach to reduce model error effects in ENSO forecasting. Weather Forecast, 34: 1321–1342
Tao L, Duan W, Vannitsem S. 2020. Improving forecasts of El Niño diversity: A nonlinear forcing singular vector approach. Clim Dyn, 55: 739–754
Tippett M K, Barnston A G. 2008. Skill of multimodel ENSO probability forecasts. Mon Wea Rev, 136: 3933–3946
Wang B, Lee J Y, Kang I S, Shukla J, Park C K, Kumar A, Schemm J, Cocke S, Kug J S, Luo J J, Zhou T, Wang B, Fu X, Yun W T, Alves O, Jin E K, Kinter J, Kirtman B, Krishnamurti T, Lau N C, Lau W, Liu P, Pegion P, Rosati T, Schubert S, Stern W, Suarez M, Yamagata T. 2009. Advance and prospectus of seasonal prediction: Assessment of the APCC/CliPAS 14-model ensemble retrospective seasonal prediction (1980–2004). Clim Dyn, 33: 93–117
Webster P J, Yang S. 1992. Monsoon and ENSO: Selectively interactive systems. Q J R Met Soc, 118: 877–926
Wilks D S. 2011. Statistical methods in the atmospheric sciences. Int Geophys Ser, vol 100, 3rd ed. Academic Press, San Diego
Yang D, Yang X Q, Xie Q, Zhang Y, Ren X, Tang Y. 2016. Probabilistic versus deterministic skill in predicting the western North Pacific-East Asian summer monsoon variability with multimodel ensembles. J Geophys Res Atmos, 121: 1079–1103
Yang D, Yang X Q, Ye D, Sun X, Fang J, Chu C, Feng T, Jiang Y, Liang J, Ren X, Zhang Y, Tang Y. 2018. On the relationship between probabilistic and deterministic skills in dynamical seasonal climate prediction. J Geophys Res-Atmos, 123: 5261–5283
Yang D, Tang Y, Yang X Q, Ye D, Liu T, Feng T, Yan X, Sun X, Zhang Y. 2021. A theoretical relationship between probabilistic relative operating characteristic skill and deterministic correlation skill in dynamical seasonal climate prediction. Clim Dyn, 56: 3909–3932
Zhang R H, Zebiak S E, Kleeman R, Keenlyside N. 2003. A new intermediate coupled model for El Niño simulation and prediction. Geophys Res Lett, 30: 2012
Zhang R H, Gao C. 2016. The IOCAS intermediate coupled model (IOCAS ICM) and its real-time predictions of the 2015–2016 El Niño event. Sci Bull, 61: 1061–1070
Zhang R H, Gao C, Feng L. 2022. Recent ENSO evolution and its real-time prediction challenges. Natl Sci Rev, 9: nwac052
Zheng F, Zhu J, Wang H, Zhang R H. 2009. Ensemble hindcasts of ENSO events over the past 120 years using a large number of ensembles. Adv Atmos Sci, 26: 359–372

(Responsible editor: Mu MU)

中国科学: 地球科学 2023 年 第 53 卷 第 6 期: 1235 ~ 1245
SCIENTIA SINICA Terrae earthcn.scichina.com
《中国科学》杂志社
SCIENCE CHINA PRESS

论 文

一个ENSO多模式集合预报系统介绍

刘婷[1,2], 高艳秋[1,2], 宋讯殊[1,2], 高川[3,9], 陶灵江[4], 唐佑民[5,6*], 段晚锁[7], 张荣华[8,9], 陈大可[1,2†]

1. 自然资源部第二海洋研究所, 卫星海洋环境动力学国家重点实验室, 杭州 300012;
2. 南方海洋科学与广东省实验室(珠海), 珠海 519000;
3. 中国科学院海洋研究所, 海洋环流与波动重点实验室, 中国科学院海洋大科学研究中心, 青岛 266071;
4. 复旦大学大气与海洋科学系, 大气科学研究院, 上海 200438;
5. 河海大学海洋学院, 南京 210098;
6. Environmental Science and Engineering, University of Northern British Columbia, Prince George, British Columbia V2N 4Z9, Canada;
7. 中国科学院大气物理研究所, 大气科学和地球流体力学数值模拟国家重点实验室, 北京 100029;
8. 南京信息工程大学海洋科学学院, 南京 210044;
9. 崂山实验室, 青岛 266237
* 通讯作者, E-mail: ytang@unbc.ca
† 通讯作者, E-mail: dchen@sio.org.cn

收稿日期: 2022-10-31; 收修改稿日期: 2023-03-06; 接受日期: 2023-03-27; 网络版发表日期: 2023-05-15
自然资源部第二海洋研究所"青年英才"项目(编号: QNYC2101)、南方海洋科学与工程广东省实验室(珠海)青年人才支持项目(编号: SML2021SP310)、国家自然科学基金重大项目(批准号: 41690124, 41690120)、国家重点研发计划"全球变化及应对"重点专项项目(编号: 2017YFA0604202)、南方海洋科学与工程广东省实验室(珠海)创新团队项目(编号: 311021001)、国家自然科学基金重点项目(批准号: 42030410)、崂山实验室专项经费项目(编号: LSL202202402)和南京信息工程大学人才引进启动项目资助

摘要 厄尔尼诺-南方涛动(El Niño and Southern Oscillation, 简称ENSO)是短期气候预测的主要可预报性来源. 为提高ENSO的预报水平, 我们构建了一个包含5个动力耦合模式的多模式集合预报系统, 其中各个模式具有不同的复杂程度、参数化方案、分辨率、初始化和集合扰动生成方案, 以尽可能全面地考虑各种不确定性对预报结果的影响. 回报试验结果表明: 多模式集合的预报效果明显好于任何一个单一模式, 其显著降低了均方根误差, 并提高了异常相关性技巧. 该多模式集合的预报效果可以比肩甚至优于同期北美多模式比较计划中的ENSO多模式集合预报技巧. 此外, 多模式集合预报能够削弱"春季预报障碍"的影响, 提供更为可靠的概率预报. 实时预报能够提前六个月准确地捕捉到近期连续两年的拉尼娜事件, 并且该系统从2022年4月开始的预报也显示出连续三年拉尼娜事件的可能性. 总体来说, 这一多模式集合预报系统能够提供比任何模式成员更加准确的确定性预报和概率预报. 这些改进主要得益于: 一方面不同模式之间的优势互补增加了可预报信息, 另一方面该系统集合成员规模较大有助于更为合理地刻画预报不确定性的分布.

关键词 多模式集合, ENSO, 预报

中文引用格式: 刘婷, 高艳秋, 宋讯殊, 高川, 陶灵江, 唐佑民, 段晚锁, 张荣华, 陈大可. 2023. 一个ENSO多模式集合预报系统介绍. 中国科学: 地球科学, 53(6): 1235–1245, doi: 10.1360/N072022-0312
英文引用格式: Liu T, Gao Y, Song X, Gao C, Tao L, Tang Y, Duan W, Zhang R H, Chen D. 2023. A multi-model prediction system for ENSO. Science China Earth Sciences, 66(6): 1231–1240, https://10.1007/s11430-022-1094-0

1 引言

厄尔尼诺-南方涛动(El Niño and Southern Oscillation, 简称ENSO)是热带太平洋上最为显著的大尺度海气耦合现象，一般2~7年发生一次. 与ENSO相关的热源强迫可以影响大气环流，并成为全球气候异常的主要驱动因子. ENSO也因此被视为季节乃至年际尺度上全球气候可预测性的首要来源(McPhaden等，2006). 能否提前预测即将到来的ENSO冷暖位相对于区域短期气候预测至关重要，有助于有效预防相关气候灾害以及减轻灾害带来的生命财产损失. 受到Cane等(1986)先驱性工作的鼓舞，经过几代人的不懈努力，ENSO预测在过去几十年取得了显著成就. 目前，国际上多家业务中心和科研机构已构建多个不同复杂程度的统计模型和动力模式，并每月定期发布实时的ENSO预测结果(Barnston等，2012; Tang等，2018; Ren等，2019)，能够提前6~12个月提供有效的ENSO预报. 但是，ENSO预测仍然面临诸多挑战，例如：初始条件的不确定性、ENSO自身的多样性以及模式对于ENSO相关物理过程刻画的局限性等(Tang等，2018; Ren等，2019)都制约了ENSO的预报水平. 以2015~2016年的超强厄尔尼诺为例，绝大多数的统计模型和动力模式提前一年均漏报了这次事件. 即使2015年夏季开始的预报抓住了当年冬季赤道中东太平洋海温的正异常演化，但不同模式预测的暖海温异常强度依然具有很大的分歧. 因此，无论是从科学角度还是社会角度出发，提高ENSO预报的准确性将是大气海洋领域永恒的焦点议题.

多模式集合是应对ENSO预测不确定性的有效手段. 多模式集合是指采用来自不同模式、不同初始条件的多个集合成员表征某一事件未来多种可能的发展轨迹. 这些模式具有不同的分辨率、参数化方案、包含不同的物理过程和初始状态，可以优势互补. 多模式集合的核心思想是尽可能全面地考虑初始条件不确定性和模式误差不确定性对预报结果的影响. 通过多模式集合平均，可以抵消一部分的模式间误差，进而提供补偿的可预报性信息(Hagedorn等，2005; Tippett和Barnston，2008; DelSole等，2014). 此外，通过扩充多模式集合的模式成员数量，也能够有效避免某一特定模式的系统性偏差对预报概率分布的影响，进而有助于更好地度量预报的不确定性. 因此，多模式集合方法通常优于单模式集合，并能够为ENSO相关的气候风险管理提供更有价值的决策信息(Wang等，2009; Becker等，2014; Min等，2014). 目前包括欧洲中长期天气预测中心(European Centre for Medium-Range Weather Forecasts, 简称ECMWF, Palmer等, 2004)、亚太经合组织气候中心(Asia-Pacific Economic Cooperation Climate Center , 简称APCC, Jeong等, 2012)、国际气候与社会研究所(International Research Institute for Climate and Society, 简称IRI, Barnston等, 2012)以及国家气象局气候中心(National Climate Center of the China Meteorological Administration, 简称NCC/CMA, Ren等，2019)等多个业务中心和研究机构都发展了各自的多模式集合短期气候预测系统. IRI从2012年开始定期发布包含全球17个动力模式和7个统计模式的ENSO多模式集合预测结果(https://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/?enso-sst_table). 近期，NCC/CMA发展了第一代中国多模式集合预测系统，包含13个动力模式、4个统计模型和3个混合模式，并逐月实时提供ENSO多模式集合预测结果(http://ncclcs.ncc-cma.net/Website/?ChannelID=254). 以上两个多模式集合系统也为目前ENSO业务化展望提供了重要参考.

与国际上相比，我国的ENSO多模式集合预测尚处于起步阶段. 受到前人工作的鼓舞，我们开发了一个多模式集合ENSO预测系统，其包含了从中等复杂程度至全球环流耦合在内的5个动力模式，采用了新的模式(Song等，2018)、新的集合预报方法(Liu等，2019，2022)、新的参数化方案(Zhang和Gao，2016; 高川等，2022)以及新的数据同化方法(Duan和Zhou, 2013; Tao和Duan, 2019; Gao等, 2020; Duan等, 2022; Song等, 2022). 我们开展了过去137年(1881~2017)的回报试验以评估ENSO预报技巧. 该系统于2020年10开始业务化试运行，并逐月发布实时的多模式集合ENSO预报结果. 本文详细了介绍该系统的进展，具体包括各个模式的详细信息、多模式集合预报系统的构建、回报数据、预报技巧评价指标、历史回报的表现以及实时预报结果.

2 数据和方法

2.1 多模式集合预报系统

本文构建的多模式集合预报系统包含三个热带太

平洋区域的中等复杂程度海气耦合模式，一个热带区域的中等复杂程度海气耦合模式以及一个全球环流耦合模式. 模式一(M1)是在LDEO 5模式(Chen等, 2004)的基础上, 将原模式的Nudging同化方案替换为集合卡尔曼滤波(EnKF)方案，并利用随机最优扰动方法(Stochastic optimal, 简称SO, Kleeman和Moore, 1997)度量大气过程的不确定性对ENSO预报结果的影响，将原模式的单一预报发展成为集合预报(Tang等, 2018; Liu等, 2019; Gao等, 2020). 模式二(M2)是Zhang等(2003)发展的，从2003年以来一直定期开展实时ENSO预测，并被IRI收录. 通过ENSO模拟和回报试验对模式参数进行优化后，该模式被中国科学院海洋研究(Institute of Oceanology, Chinese Academy of Sciences, 简称IOCAS)所使用, 并命名为IOCAS ICM. 该模式从2015年8月开始定期发布热带太平洋海温的预测结果(Zhang和Gao, 2016; Zhang等, 2022). 模式三(M3)是在M2的基础上, 利用非线性强迫奇异向量这一新的数据同化方法，添加模式倾向扰动来联合度量初始误差和模式误差对预报结果的影响(Duan和Zhou, 2013; Tao和Duan, 2019; Duan等, 2022). 该模式能够提前两个季节预测不同类型ENSO(Tao等, 2020). 模式四(M4)是将经典的Zebiak-Cane模式(Cane等, 1986)的物理框架从太平洋拓展到整个热带区域. 通过表层风场偏差订正以及地表热通量参数化等改进，提高了对整个热带海温变率和海盆间相互作用模拟的准确性(Song等, 2018). 模式五(M5)是CESM 1.2, 为目前被广泛使用的地球系统模式，也是目前国家海洋环境预报中心的业务预测模式(李熠等, 2015). 我们通过调整次表层的Nudging同化系数以及添加大气风场同化模块改进了国家海洋环境预报中心的同化方案，改善了预报初始场的质量, 提高了ENSO的模拟和预测能力. 同时还利用气候相关的奇异向量方法(Climatically relevant singular vector, 简称CSV, Kleeman等, 2003)为M5生成集合初始扰动，与单一模式预测相比，这能够有效提升ENSO预测技巧(Liu等, 2022). 更详细的模式信息如表1所示. 总体来说，这一多模式集合预报系统通过采用了具有不同复杂程度、分辨率、物理参数化方案、资料同化方法、初始化资料以及集合扰动生成策略的多个模式，可尽可能全面地考虑各种不确定性对预报结果的影响.

从1881年到2017年，M1到M5从每年1月1日、4月1日、7月1日和10月1日进行时长为12个月的回报试验. 为了消除模式系统偏差, 每个模式的异常值定义为其原始回报数据减去自身的气候态. 各个模式通过等权重方案进行多模式集合. 由于M1和M5自身具有集合预报系统，因此他们各自的集合平均用来进行多模式集合.

2.2　方法

本文中确定性预报技巧采用异常相关系数(anomaly correlation coefficient, 简称ACC)和均方根误差(root mean square error, 简称RMSE)来度量:

$$ACC(t)=\frac{\sum_{i=1}^{N}\left[x_i^f(t)-\overline{x^f}(t)\right]\left[x_i^o(t)-\overline{x^o}(t)\right]}{\sqrt{\sum_{i=1}^{N}\left[x_i^f(t)-\overline{x^f}(t)\right]^2}\sqrt{\sum_{i=1}^{N}\left[x_i^o(t)-\overline{x^o}(t)\right]^2}}, \tag{1}$$

$$RMSE(t)=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_i^f(t)-\overline{x^f}(t)\right)^2}, \tag{2}$$

其中，$x_i^f(t)$和$x_i^o(t)$分别表示某一变量的第i个初始条件预报到第t个月的多模式集合平均的预测和对应的观测结果. $\overline{x^f}$和$\overline{x^o}$分别代表模式和观测气候态. N表示回报总次数, 即137年×4次/年=548次.

概率预报技巧的评价采用Brier技巧评分(Brier skill score, 简称BSS, Wilks 2011), 其评估了相对于参考气候态的Brier评分(Brier score, 简称BS), 即度量预报概率分布和观测频率之间的均方误差:

$$\begin{aligned}BS&=\frac{1}{N}\sum_{m=1}^{M}n_m(\bar{x}_m-\bar{o}_m)^2\\&\quad-\frac{1}{N}\sum_{m=1}^{M}n_m(\bar{o}_m-\bar{o})^2+\bar{o}(1-\bar{o}),\end{aligned} \tag{3}$$

$$BSS=1-\frac{BS}{BS_{CLM}}, \tag{4}$$

其中，x和o分别表示某一事件的预测概率和观测频次. M表示从0.1到1.0且间隔为0.1的概率区间数目. $\bar{x}_m$和$\bar{o}_m$是指落入第m个概率区间的所有预报和对应的观测的均值，n_m是落入该区间的预测个数. N表示预测总次数. $\bar{o}$代表$\bar{o}_m$的均值，表示观测到的气候态概率. 通常情况下$BS_{CLM}=\bar{o}(1-\bar{o})$，因此$BSS$表示相对于气候态预测，概率预报的改进能力, BSS为正说明概率预测有效, BSS为负说明概率预测不如气候态预测.

表 1　多模式集合预测系统中各模式信息介绍[a)]

模式	模式类型	模式区域	资料同化	集合扰动生成方案
M1	中等复杂程度	热带太平洋	EnKF 大气: ERA-20C UV 海洋: Kaplan SST	EnKF+SOs
M2	中等复杂程度	热带太平洋	线性差值 海洋: Kaplan SST	/
M3	中等复杂程度	热带太平洋	Nudging 海洋: ERSST V5 SST	/
M4	中等复杂程度	热带	Nudging 海洋: Kaplan SST	/
M5	全球环流耦合	全球	Nudging 大气: ERA-20C + ERA-Interim UV 海洋: SODA+GODAS sea temperature	CSVs

a) SO: 随机最优扰动方法(Kleeman和Moore, 1997); CSV: 气候相关的奇异向量方法(Kleeman等, 2003)

我们采用Niño 3.4指数表征ENSO变率. 冷事件、中性事件和暖事件的定义与前人研究一致(Yang等, 2016, 2018; Liu等, 2019; Yang等, 2021), 即分别取1881到2017年间观测的Niño3.4指数气候态分布的下、中、上三分之一分位数为划分标准. 模式第一个月回报输出定义为提前一个月的预报. 回报结果评估用到的观测资料选用模式同化使用较多的Kaplan SST V2数据集(Kaplan等, 1998).

3　多模式集合预报系统中ENSO的表现

3.1　多模式集合预报提高确定性预报水平

图1为多模式集合平均的Niño 3.4指数预测(蓝线)和对应观测(红线)的时间序列. 整体而言, 在过去的137年里, 多模式集合预报系统能够提前一年预测大多数ENSO事件, 尤其是显著的冷、暖事件. 在提前6个月的回报中, 预测结果与观测基本吻合, 相关系数可以达到0.83. 在提前12个月的回报中, 尽管观测值和预测之间的一致性有一定程度的退化, 但相关系数也能达到0.59. 该系统可以相对较好地捕捉到观测中主要的厄尔尼诺和拉尼娜事件, 但随着预报提前期的增加, 对于ENSO事件强度的预测有低估的趋势. 图2展示的是多模式集合平均(红线)和各个模式(彩色线)预测的Niño 3.4指数与对应观测之间的相关系数和均方根误差. 总体而言, 无论是相关系数还是均方根误差, 多模式集合预测均表现出明显的优势, 即具备更高的相关系数与更低的均方根误差. 该系统能够提前12个月给出有效的ENSO预测结果(相关系数>0.5). 在北美多模式集合试验验证时段(1982~2010, Kirtman等, 2014), 该多模式集合预测仍然具有比其任何一个模式成员更好的相关系数和均方根误差技巧(图3), 提前3、6和9个月预测的相关系数技巧分别能够达到0.95、0.87和0.76, 这持平甚至优于北美多模式集合预测的水平(3、6和9个月预测的相关系数分别为0.91、0.83和0.7, Barnston等, 2019). 简而言之, 以上回报试验的结果证明了多模式集合方法的优越性. 通过这一方法各模式之间可以优势互补, 降低单一模式误差对预报结果的影响. 在ENSO预测方面, 我们的多模式集合预测结果可以比肩甚至优于北美多模式集合. 这一令人鼓舞的结果也增加了我们将其应用于ENSO实时预测的信心.

3.2　多模式集合预报改善春季预报障碍

众所周知, ENSO预测存在明显的季节变化, 称之为“春季预报障碍” (Webster和Yang, 1992). 可以看出在我们的多模式系统中, 每个模式都存在不同程度上的“春季预报障碍”(图4), 即无论从何时起报, 当跨域春季时预报技巧均呈现明显下降; 并且与7月和10月起报相比, 1月和4月起报的技巧在春季下降更快. 即便如此, 多模式集合平均的结果也优于任何一个模式, 预报技巧在春季下降更为缓慢. 多模式集合平均的有效预测时长(相关系数>0.5)明显好于任何一个模式.

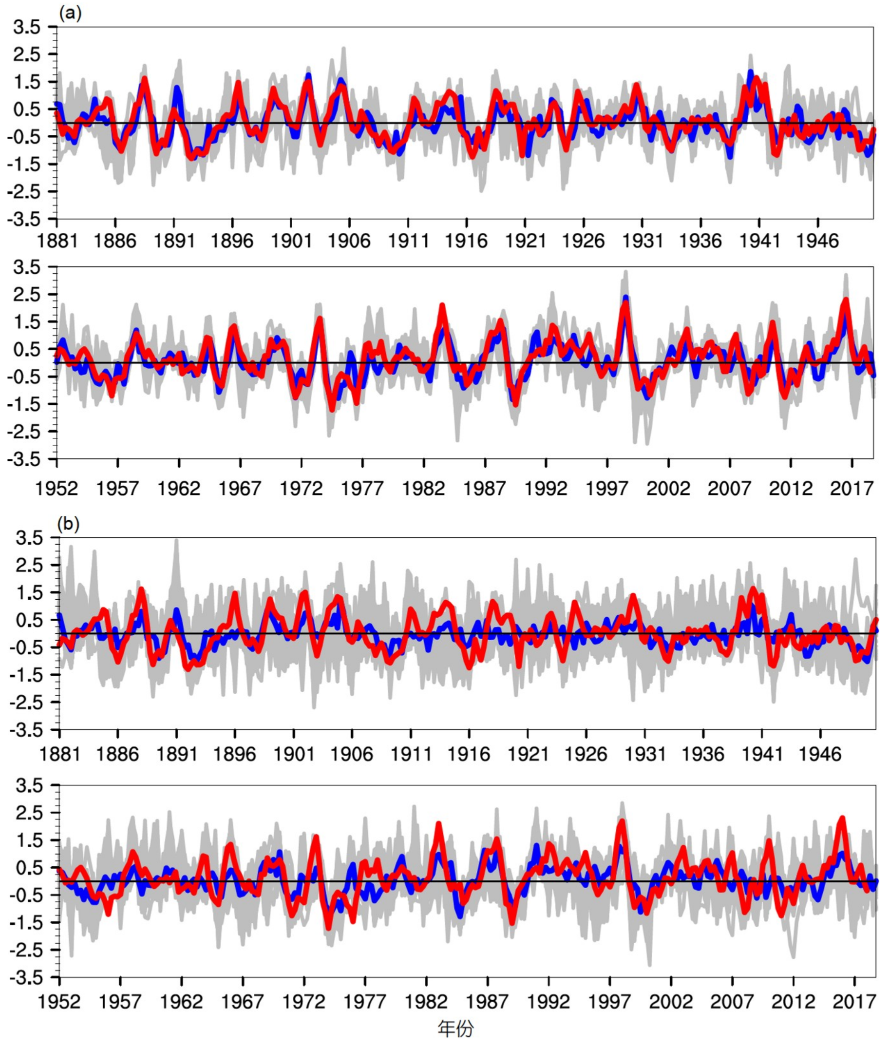

图 1　多模式集合系统提前6个月(a)和提前12个月(b)预测的Niño 3.4指数和对应观测的时间序列

红线和蓝线分别代表观测和预测结果, 灰色阴性表示集合预报的离散度

以上结果表明: 多模式集合平均能够明显削弱"春季预报障碍"的影响, 提高预报的准确性. 这一改善主要得益于经过多模式平均之后, 不同模式间的误差相互抵消, 减少了模式误差对预报结果的影响, 提供了额外的可预测信号(Palmer等, 2004; Hagedorn等, 2005; DelSole等, 2014). 因此, 多模式集合是改善"春季预报障碍", 提高预测ENSO水平的有效工具.

3.3　多模式集合预报提高概率预报水平

在该多模式集合系统中, M1和M5拥有各自的集合预报系统, 分别包含100个和20个集合成员. 因此我们也可以评估多模式集合(共计123个集合成员)相比于单模式集合在概率预报方面的改进情况. 图5分别展示了多模式集合(红线)、M1(绿线)和M5(蓝线)预测Niño3.4指数的BSS评分. 可以看出, 多模式集合预报改善了在所有预报时长下对冷、暖、中性事件预测的BSS技巧. 同时, 多模式集合可以提前11个月提供中性事件的有效概率预报结果(BSS>0), 与任何一个单一模式的集合预报相比, 这是一个实质性的改进. 可靠性和分辨力是概率预报的两大特征. 可靠性表示事件的预测概率与该事件的观测频率之间的差异. 分辨力度量的是预报系统不同于气候态预报的能力. 多模式集合可以同时改进概率预报的分辨力(图6)和可靠性(图7), 其中最为明显的是提高了概率预测的可靠性. 上述改

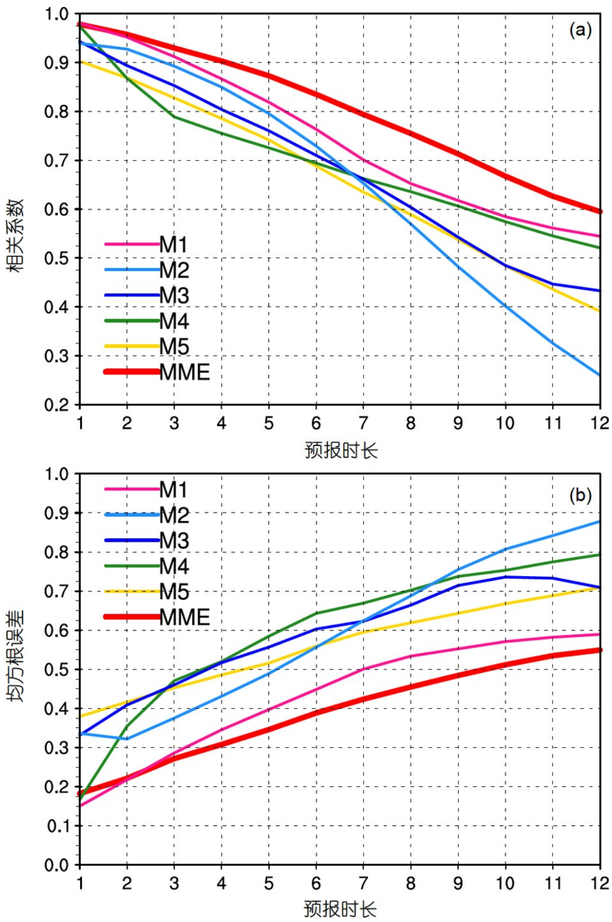

图 2　1881~ 2017年期间多模式集合系统预测的Niño3.4指数与对应观测值的相关系数(a)和均方根误差(b)

粗红线代表多模式集合平均的结果, 彩色线代表各个模式的结果

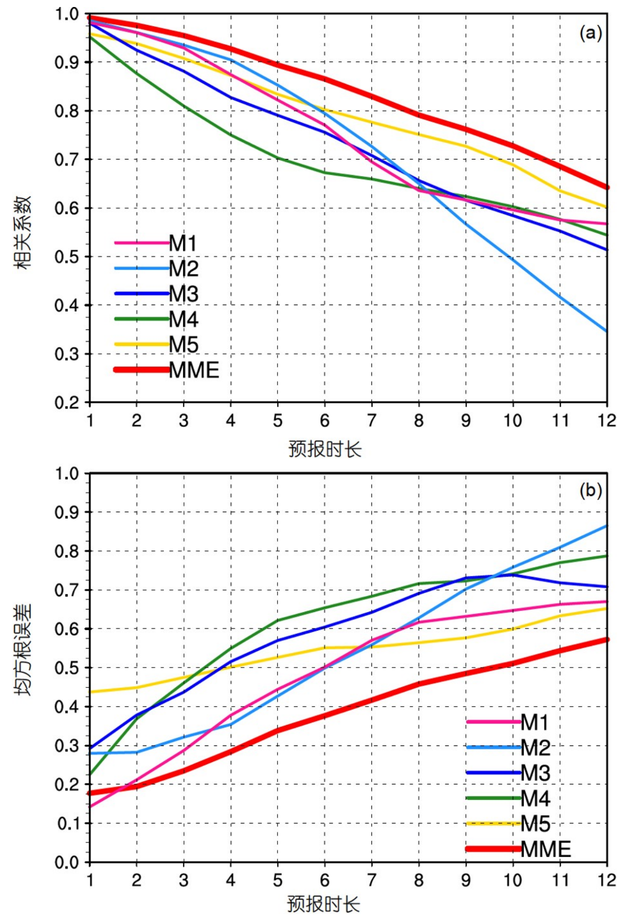

图 3　1982~2010年期间多模式集合系统预测的Niño3.4指数与对应观测值的相关系数(a)和均方根误差(b)

粗红线代表多模式集合平均的结果, 彩色线代表各个模式的结果

进主要是由于多模式集合扩大了集合成员的样本空间, 有助于更合理地刻画预报的不确定性分布, 从而提供更可靠的概率预报结果. 除上述两个指标, ROC评分(Mason和Graham, 1999)也是一种被广泛使用的概率预报度量指标(Dewitt, 2005; Chen和Cane, 2008; Zheng等, 2009), 其本质含义与BSS分辨力项一致(Yang等, 2021). 多模式集合针对冷、暖、中性事件的ROC技巧同样在所有预报时长下均优于任何一个单一模式的集合预报(图未显示). 这进一步表明, 多模式集合能够提供更为有效的概率预报结果, 具有比任何一个单一模式更高的潜在经济价值.

3.4　多模式集合预报的实时预报

基于这一多模式集合系统, 我们从2020年10月起在自然资源部第二海洋研究所卫星海洋环境动力学国家重点实验室网站逐月发布实时的ENSO预测结果(https://soed.sio.org.cn/emsodm.html), 并参加国家海洋环境预报中心和国家气候中心组织的ENSO会商, 提供预测意见. 在过去一年多时间里, 实时预测准确地预测了赤道中东太平洋海温的演变. 多模式集合预测准确地抓住了最近连续两年的拉尼娜事件(图8). 从2021年6月开始, 多模式集合预测稳定捕捉到赤道中东太平洋海温二次变冷的趋势; 从2022年4月开始, 多模式集合预测也预告了即将到来的三次变冷的可能性, 这也是进入20世纪以来的第一次连续三年拉尼娜事件. 此外, 多模式集合预测结果也与过去一年多IRI发布的预测结果保持一致. 但由于“春季预报障碍”的影响, 预测结果仍存在一定的不确定性, 跨越春季的

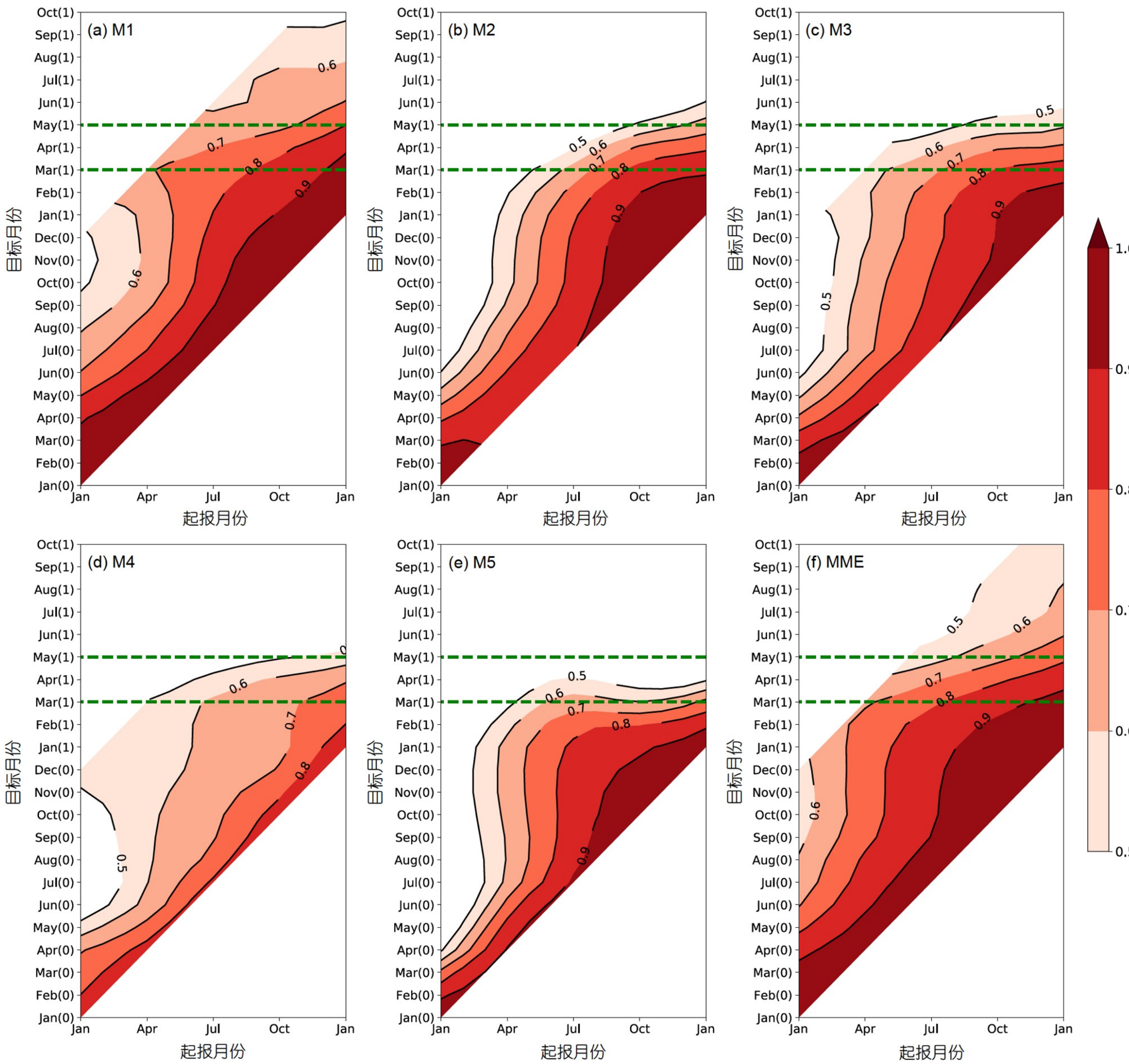

图 4　M1~M5((a)~(e))以及多模式集合系统(f)不同月份起报的Niño3.4指数与对应观测的相关系数技巧随时间的变化

预报效果差于全年其他时刻的预报. 尽管如此, 多模式集合在春季的预测结果依然更加接近实况, 好于任何一个单一模式结果.

4　总结和讨论

ENSO冷、暖事件相关的海温强迫能够激发大气环流响应, 是进行短期气候预测的基础. 因此, 能否提前准确预测ENSO变得至关重要, 这在气候灾害, 防灾减灾方面具有巨大的经济和社会价值. 初始条件的不确定性、模式误差以及海气耦合系统自身的混沌行为均可影响ENSO的预测能力. 多模式集合方法是提高ENSO预测水平的有效工具(Barnston等, 2012; Kirtman等, 2014; Barnston等, 2019). 其可充分发挥所有模式集合成员的潜力, 更好地刻画预报的概率分布, 降低预报误差并量化预测不确定性. 本文介绍了我们最近发展的ENSO多模式集合预测系统, 该系统包含5个采用不同物理过程、参数化方案、分辨率、集合扰动生

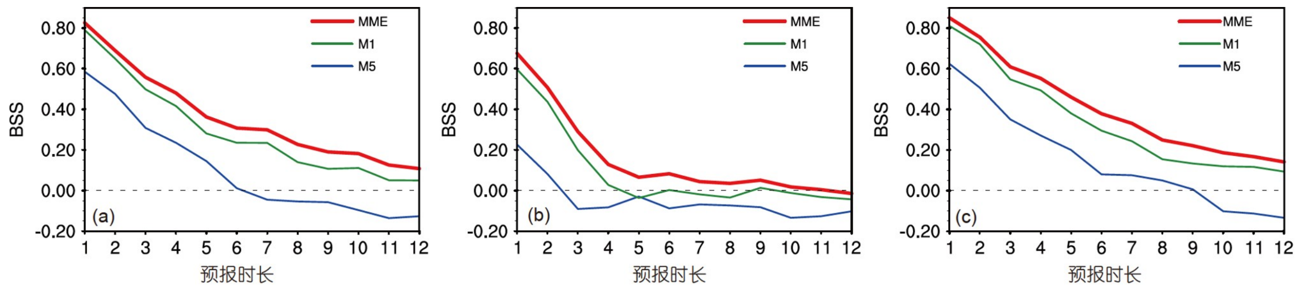

图 5 冷事件(a)、中性事件(b)、暖事件(c)的M1和M5以及多模式集合预测MME的BSS评分随预报时间的变化

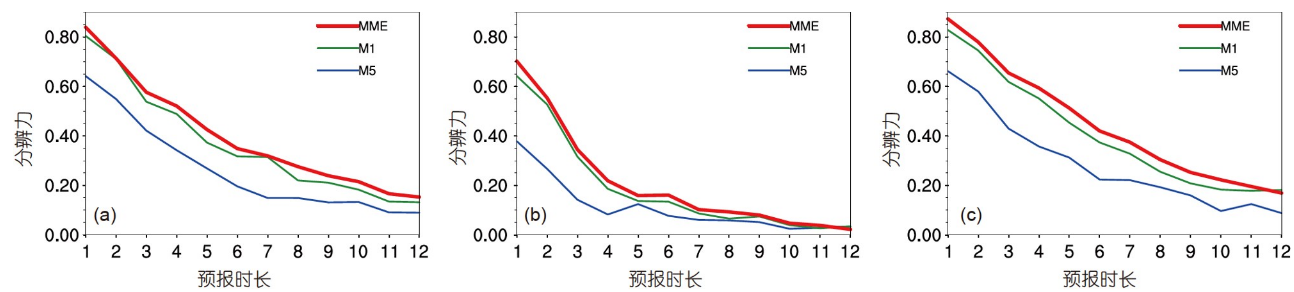

图 6 冷事件(a)、中性事件(b)、暖事件(c)的M1和M5以及多模式集合预测MME的分辨力评分随预报时间的变化

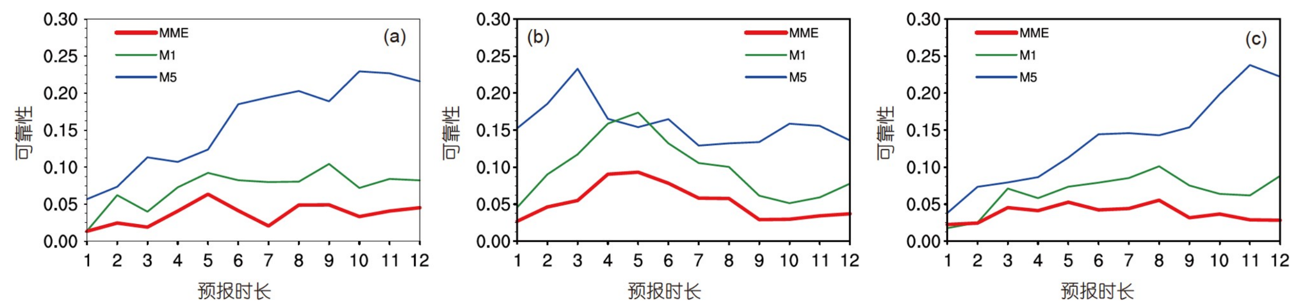

图 7 冷事件(a)、中性事件(b)、暖事件(c)的M1和M5以及多模式集合预测MME的可靠性评分随预报时间的变化

成方案、同化方法以及不同观测资料的动力耦合模式. 这一集合方案旨在尽可能全面地考虑各种来源的不确定性对预报结果可能造成的影响. 我们开展了长期的回报试验, 并评估了其确定性预报和概率预报的技巧. 结果表明, 多模式集合预测具有明显的优势, 主要体现在:

(1) 相比于任何一个单一模式, 多模式集合预测可以明显提高相关系数, 降低均方根误差; 其ENSO预测水平可以比肩甚至优于北美多模式集合预测.

(2) 相比于任何一个单一模式, 多模式集合预测可以削弱"春季预报障碍"的影响, 在跨越春季时预报技巧下降较慢, 其有效预测时长得以明显提高.

(3) 多模式集合具备更高的概率预测技巧, 可以同时改善可靠性和分辨力两项指标, 其中可靠性的改善尤为突出.

(4) 多模式集合成功预测出近期连续两年的拉尼娜事件, 提前6个月捕捉到了赤道中东太平洋海温二次变冷的趋势. 从2022年4月以来, 该系统也提示了即将连续三年拉尼娜事件的可能性.

总体来说, 该多模式集合系统的ENSO预报效果好于系统任何一个单一模式, 能够提供更为合理的确定性预报和概率预报结果. 这些改进得益于: 一方面

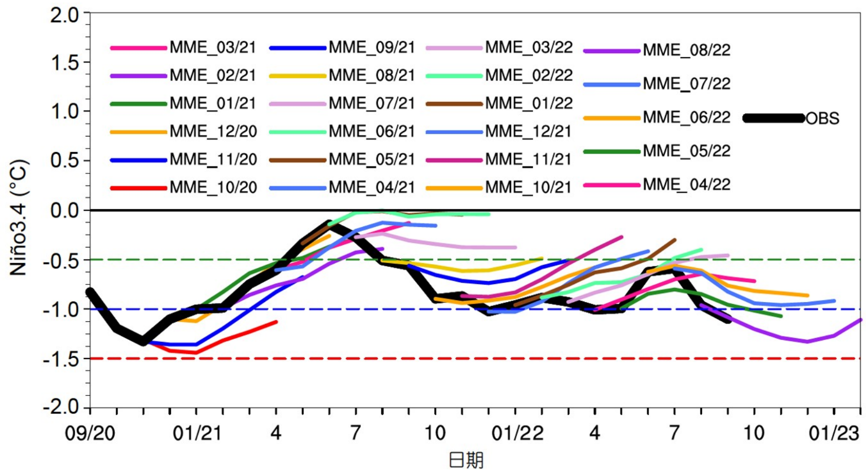

图 8 2020年10月开始, 多模式集合系统每个月预测的Niño3.4指数(彩色线)与观测实况(黑线)

多模式集合平均抵消了部分模式误差的影响，增加了额外的可预报信息；另一方面多模式集合能够扩充集合成员样本空间，有助于更为合理地刻画预报不确定性的分布．因此，多模式集合方法是一种有效且实用的ENSO业务预测策略，可为决策者及用户提供潜在的经济和科学价值．然而，该多模式集合预测系统目前仍处于初期阶段，还有待进一步发展完善．未来将考虑以下两种可能的方案以进一步减少预测误差．一方面，通过引入先进的经验后处理技术去订正预报结果；另一方面，基于“超级集合预报”思想(Krishnamurti等, 1999, 2016), 根据每个模式的历史表现, 采用线性或非线性方法为模式集合分配最优权重．ENSO多模式集合预测在我国起步较晚，未来还需要持续增加投入，开展深入研究．希望通过不懈努力, 我们的多模式集合预报系统能够及时、准确地发布ENSO预报结果，为业务预测和防灾减灾提供可靠支持．

致谢 感谢两位匿名审稿人对提升本文质量所提出的意见和建议．

参考文献

李熠，陈幸荣，谭晶，黄勇勇，蔡怡. 2015. 基于CESM气候模式的ENSO后报试验. 海洋学报, 37: 39–50

高川, 陈茂楠, 周路, 冯立成, 张荣华. 2022. 2020~2021年热带太平洋持续性双拉尼娜事件的演变. 中国科学: 地球科学, 52: 2353–2372

Becker E, den Dool H, Zhang Q. 2014. Predictability and forecast skill in NMME. J Clim, 27: 5891–5906

Barnston A G, Tippett M K, L'Heureux M L, Li S, DeWitt D G. 2012. Skill of real-time seasonal ENSO model predictions during 2002–2011: Is our capability increasing? Bull Am Meteorol Soc, 93: 631–651

Barnston A G, Tippett M K, Ranganathan M, L'Heureux M L. 2019. Deterministic skill of ENSO predictions from the North American Multimodel Ensemble. Clim Dyn, 53: 7215–7234

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

Chen D, Cane M A, Kaplan A, Zebiak S E, Huang D. 2004. Predictability of El Niño over the past 148 years. Nature, 428: 733–736

Chen D, Cane M A. 2008. El Niño prediction and predictability. J Comput Phys, 227: 3625–3640

DelSole T, Nattala J, Tippett M K. 2014. Skill improvement from increased ensemble size and model diversity. Geophys Res Lett, 41: 7331–7342

Dewitt D G. 2005. Retrospective forecasts of interan nual sea surface temperature anomalies from 1982 to present using a directly coupled atmosphere-ocean general circulation model. Mon Weather Rev, 133: 2972–2995

Duan W, Zhou F. 2013. Non-linear forcing singular vector of a two-dimensional quasi-geostrophic model. Tellus A, 65: 18452

Duan W, Feng R, Yang L, Jiang L. 2022. A new approach to data assimilation for numerical weather forecasting and climate prediction. J Appl Anal Comput, 12: 1007–1021

Gao Y, Liu T, Song X, Shen Z, Tang Y, Chen D. 2020. An extension of LDEO5 model for ENSO ensemble predictions. Clim Dyn, 55:

2979–2991
Hagedorn R, Doblas-reyes F J, Palmer T N. 2005. The rationale behind the success of multi-model ensembles in seasonal forecasting—I. Basic concept. Tellus A, 57: 219–233
Jeong H I, Lee D Y, Ashok K, Ahn J B, Lee J Y, Luo J J, Schemm J K E, Hendon H H, Braganza K, Ham Y G. 2012. Assessment of the APCC coupled MME suite in predicting the distinctive climate impacts of two flavors of ENSO during boreal winter. Clim Dyn, 39: 475–493
Kaplan A, Cane M A, Kushnir Y, Clement A C, Blumenthal M B, Rajagopalan B. 1998. Analyses of global sea surface temperature 1856–1991. J Geophys Res, 103: 18567–18589
Kirtman B P, Min D, Infanti J M, Kinter James L. I, Paolino D A, Zhang Q, van den Dool H, Saha S, Mendez M P, Becker E, Peng P, Tripp P, Huang J, DeWitt D G, Tippett M K, Barnston A G, Li S, Rosati A, Schubert S D, Rienecker M, Suarez M, Li Z E, Marshak J, Lim Y K, Tribbia J, Pegion K, Merryfield W J, Denis B, Wood E F. 2014. The North American multimodel ensemble: Phase-1 seasonal-to-interannual prediction; Phase-2 toward developing intraseasonal prediction. Bull Amer Meteor Soc, 95: 585–601
Kleeman R, Moore A M. 1997. A theory for the limitation of ENSO predictability due to stochastic atmospheric transients. J Atmos Sci, 54: 753–767
Kleeman R, Tang Y, Moore A M. 2003. The calculation of climatically relevant singular vectors in the presence of weather noise. J Atmos Sci, 60: 2856–2868
Krishnamurti T N, Kishtawal C M, LaRow T E, Bachiochi D R, Zhang Z, Williford C E, Gadgil S, Surendran S. 1999. Improved weather and seasonal climate forecasts from multimodel superensemble. Science, 285: 1548–1550
Krishnamurti T N, Kumar V, Simon A, Bhardwaj A, Ghosh T, Ross R. 2016. A review of multimodel superensemble forecasting for weather, seasonal climate, and hurricanes. Rev Geophys, 54: 336–377
Liu T, Tang Y, Yang D, Cheng Y, Song X, Hou Z, Shen Z, Gao Y, Wu Y, Li X, Zhang B. 2019. The relationship among probabilistic, deterministic and potential skills in predicting the ENSO for the past 161 years. Clim Dyn, 53: 6947–6960
Liu T, Song X, Tang Y, Shen Z, Tan X. 2022. ENSO predictability over the past 137 years based on a CESM ensemble prediction system. J Clim, 35: 763–777
McPhaden M J, Zebiak S E, Glantz M H. 2006. ENSO as an integrating concept in Earth science. Science, 314: 1740–1745
Mason S J, Graham N E. 1999. Conditional probabilities, relative operating characteristics, and relative operating levels. Weather Forecast, 14: 713–725
Min Y M, Kryjov V N, Oh S M. 2014. Assessment of APCC multimodel ensemble prediction in seasonal climate forecasting: Retrospective (1983–2003) and real-time forecasts (2008–2013). J Geophys Res Atmos, 119: 12,132–12,150
Palmer T N, Alessandri A, Andersen U, Cantelaube P, Davey M, Délécluse P, Déqué M, Díez E, Doblas-Reyes F J, Feddersen H, Graham R, Gualdi S, Guérémy J F, Hagedorn R, Hoshen M, Keenlyside N, Latif M, Lazar A, Maisonnave E, Marletto V, Morse A P, Orfila B, Rogel P, Terres J M, Thomson M C. 2004. Development of a european multimodel ensemble system for seasonal-to-interannual prediction (Demeter). Bull Am Meteorol Soc, 85: 853–872
Ren H L, Wu Y, Bao Q, Ma J, Liu C, Wan J, Li Q, Wu X, Liu Y, Tian B, Fu J X, Sun J. 2019. The China multi-model ensemble prediction system and its application to flood-season prediction in 2018. J Meteorol Res, 33: 540–552
Song X, Chen D, Tang Y, Liu T. 2018. An intermediate coupled model for the tropical ocean-atmosphere system. Sci China Earth Sci, 61: 1859–1874
Song X, Li X, Zhang S, Li Y, Chen X, Tang Y, Chen D. 2022. A new nudging scheme for the current operational climate prediction system of the National Marine Environmental Forecasting Center of China. Acta Oceanol Sin, 41: 51–64
Tang Y, Zhang R H, Liu T, Duan W, Yang D, Zheng F, Ren H, Lian T, Gao C, Chen D, Mu M. 2018. Progress in ENSO prediction and predictability study. Natl Sci Rev, 5: 826–839
Tao L J, Duan W S. 2019. Using a nonlinear forcing singular vector approach to reduce model error effects in ENSO forecasting. Weather Forecast, 34: 1321–1342
Tao L, Duan W, Vannitsem S. 2020. Improving forecasts of El Niño diversity: A nonlinear forcing singular vector approach. Clim Dyn, 55: 739–754
Tippett M K, Barnston A G. 2008. Skill of multimodel ENSO probability forecasts. Mon Wea Rev, 136: 3933–3946
Wang B, Lee J Y, Kang I S, Shukla J, Park C K, Kumar A, Schemm J, Cocke S, Kug J S, Luo J J, Zhou T, Wang B, Fu X, Yun W T, Alves O, Jin E K, Kinter J, Kirtman B, Krishnamurti T, Lau N C, Lau W, Liu P, Pegion P, Rosati T, Schubert S, Stern W, Suarez M, Yamagata T. 2009. Advance and prospectus of seasonal prediction: assessment of the APCC/CliPAS 14-model ensemble retrospective seasonal prediction (1980–2004). Clim Dyn, 33: 93–117
Webster P J, Yang S. 1992. Monsoon and ENSO: Selectively interactive systems. Q J R Met Soc, 118: 877–926
Wilks D S. 2011. Statistical methods in the atmospheric sciences. Int Geophys Ser, vol 100, 3rd ed. Academic Press, San Diego
Yang D, Yang X Q, Xie Q, Zhang Y, Ren X, Tang Y. 2016.

Probabilistic versus deterministic skill in predicting the western North Pacific-East Asian summer monsoon variability with multi-model ensembles. J Geophys Res-Atmos, 121: 1079–1103

Yang D, Yang X Q, Ye D, Sun X, Fang J, Chu C, Feng T, Jiang Y, Liang J, Ren X, Zhang Y, Tang Y. 2018. On the relationship between probabilistic and deterministic skills in dynamical seasonal climate prediction. J Geophys Res-Atmos, 123: 5261–5283

Yang D, Tang Y, Yang X Q, Ye D, Liu T, Feng T, Yan X, Sun X, Zhang Y. 2021. A theoretical relationship between probabilistic relative operating characteristic skill and deterministic correlation skill in dynamical seasonal climate prediction. Clim Dyn, 56: 3909–3932

Zhang R H, Zebiak S E, Kleeman R, Keenlyside N. 2003. A new intermediate coupled model for El Niño simulation and prediction. Geophys Res Lett, 30: 2012

Zhang R H, Gao C. 2016. The IOCAS intermediate coupled model (IOCAS ICM) and its real-time predictions of the 2015–2016 El Niño event. Sci Bull, 61: 1061–1070

Zhang R H, Gao C, Feng L. 2022. Recent ENSO evolution and its real-time prediction challenges. Natl Sci Rev, 9: nwac052

Zheng F, Zhu J, Wang H, Zhang R H. 2009. Ensemble hindcasts of ENSO events over the past 120 years using a large number of ensembles. Adv Atmos Sci, 26: 359–372

(责任编委: 穆穆)