Key Points:

• SST-nudging strength is a key parameter for initializing coupled models in ENSO prediction
• We generate an outperformed ensemble forecast with members from multiple coupled model initialization parameters
• Increasing the parameter diversity of ensemble members is a new and effective way to further improve the prediction skill of ensemble forecasts

Abstract

Accurate prediction of El Niño–Southern Oscillation (ENSO) at relatively long timescales is propitious to forecasting other climate variables and meteorological disasters. Here, we use a coupled dynamical global ocean–atmosphere coupled model, ICMv2, to investigate the influence of an initialization parameter, sea surface temperature (SST)-nudging strength, on ENSO prediction skill in the model’s 1981–2010 hindcast experiments and suggest a multiple initialization parameter ensemble (MIPE) forecast as a new ensemble forecasting strategy to improve ENSO prediction skill. Different SST-nudging strengths produce different ENSO prediction skill via the generated various initial values. Selecting initial values closest to the observed SST (represented by reanalysis data) and increasing the ensemble size is inefficient in improving the skill of single initialization parameter ensemble (SIPE) forecasts. With ensemble members from different SST-nudging strength groups, the MIPE forecasts are significantly more skillful than the SIPE forecasts at 1- to 10-month lead time. More than 96% of 20,000 MIPE experiments generated by a Monte Carlo approach have larger anomaly correlation coefficient than SIPE at 1- to 9-month lead time. Our findings suggest that MIPE forecasting is another efficient strategy that can improve ENSO prediction skill besides multimodel and multimember ensembles using different initial values with random disturbances.

1. Introduction

El Niño–Southern Oscillation (ENSO) is one of the most dominant interannual climate signals in the tropics, with global influence on atmospheric circulation and precipitation (e.g., McPhaden et al., 2006; Ropelewski & Halpert, 1987). Achieving a high level of skill in predicting ENSO is helpful for alleviating the destructiveness of ENSO-induced climate disasters (e.g., Goddard & Dilley, 2005). To date, many coupled general circulation models (CGCMs) have been applied to the seasonal prediction of ENSO, following a series of innovations and improvements in the past few decades. The Zebiak-Cane model was the first simple dynamical global ocean-atmosphere coupled model to successfully describe the basic spatial patterns and seasonal phase-locking feature of ENSO (Cane et al., 1986; Zebiak & Cane, 1987).

Initial errors will grow rapidly once the forecast starts due to the initialization shock (Mulholland et al., 2015). Therefore, an effective way to improve the ENSO prediction skill of CGCMs is to alleviate the deficiencies of the initial conditions (e.g., Buizza & Palmer, 1995; Chen et al., 1995; Chen et al., 1997; Rosati et al., 1997; Toth & Kalnay, 1993). Better observation and initialization schemes can generate more realistic initial conditions and consequently deliver a more accurate ENSO prediction because of the “memory” of ocean oscillations in the subsurface ocean thermal state (e.g., McPhaden, 2012; Neelin et al., 1998). Chen et al. (1995) nudged wind stress toward observations in the initialization process of the Zebiak-Cane model to obtain improved ENSO prediction skill, and then sea surface and subsurface temperature observations were also implemented into the oceanic assimilation (e.g., Ji et al., 1994; Ji et al., 1998; Rosati et al., 1997). Moreover, sea surface temperature (SST) nudging has become a common initialization scheme applied in many CGCMs (e.g., Keenlyside et al., 2005; Luo et al., et al., 2005; Luo et al., 2008; Moroika et al., 2014; Moroika et al., 2018; Zhu et al., 2015; Zhu et al., 2017). Keenlyside et al. (2005) used the SST-nudging scheme in MPI-OM/ECHAM5 to successfully predict ENSO at a 6-month lead time. Another CGCM, SINTEX-F, with improved climate simulation generated improved initial values...
In SST-nudging schemes, the SST-nudging strength is a key initialization parameter in the negative feedback process to surface heat fluxes and reflects the speed of the model's SST nudged toward the observations (Luo et al., 2005; Madec, 2008). In previous studies, the SST-nudging strength was often chosen as a fixed value (−2,400 W·m⁻²·K⁻¹) to generate initialization values more correlated with the observations (e.g., Luo et al., 2005; Madec, 2008; Morioka et al., 2014). The principle of SST nudging is to strongly nudge the SST in the model close to the observation. The SSTs in the oceanic model are used to drive the atmospheric model for the production of surface fluxes and the surface fluxes from the atmospheric model in turn force the oceanic model to produce the ocean heat content (e.g., Keenlyside et al., 2005; Luo et al., 2005; Morioka et al., 2018). However, the initialization values closest to observations generated by a certain fixed SST-nudging strength could also involve uncertainties, because the reanalyzed observations applied in the initialization cannot absolutely represent the actual conditions. It is not clear yet how the SST-nudging strength might influence the initialized SST values and ENSO prediction skill.

Multimodel ensemble forecasts successfully improve the ENSO prediction skill via offset uncertainties in initial conditions and model physics among the single models (e.g., Becker et al., 2014; Kumar et al., 2017; Palmer et al., 2000; Saha et al., 2014; Wang et al., 2009). Inspired by the multimodel ensemble approach, a multiple initialization parameter ensemble (MIPE) forecast with initial values generated by different SST-nudging strengths might also improve the ENSO prediction skill, because the prediction errors from uncertainties of initial conditions could be offset among ensemble members (e.g., Barnston et al., 2017; Toth & Kalnay, 1993). Here, we implement the SST-nudging scheme of a CGCM, ICMv2, to study the influence of the SST-nudging strength on the ENSO prediction skill from 1981 to 2010. The results show that the SST-nudging strength has an apparent influence on the ENSO prediction skill, and MIPE forecast can effectively improve the ENSO prediction skill. The remainder of the paper is organized as follows: In section 2, the coupled model applied in this study, ICMv2, as well as its performance, is briefly introduced. Section 3 describes the initialization process and the experimental design. Results are presented in section 4. Finally, a summary of our findings is provided in section 5.

2. Model and Data
2.1. Introduction to ICMv2
ICMv2 is a coupled atmosphere-ocean model developed on the basis of ICMv1 (Huang et al., 2014) by the Center for Monsoon System Research, Institute of Atmospheric Physics, Chinese Academy of Sciences. ICM incorporates the oceanic component NEMO 2.3 (Madec, 2008) and the atmospheric component ECHAM5 (Roeckner et al., 2003; Roeckner et al., 2006). NEMO 2.3 is a combination of an ocean model (OPA 9; Madec, 2008) and sea ice model (LIM 2; Fichefet, 1997; Bouillon et al., 2009). In ICMv2, NEMO 2.3 is set to 31 layers in the vertical direction and the horizontal resolution is approximately 2° × 0.5° near the equator and 2° × 2° at the high latitudes (Madec, 2008). ECHAM5 in ICMv2 has a horizontal resolution of 1.875° × 1.875° and 19 layers in the vertical direction, using a hybrid sigma-pressure coordinate. The atmospheric and oceanic models using the SST-nudging scheme. In the ensemble forecast of SINTEX-F, the anomaly correlation coefficient (ACC) of predicted Niño3.4 index can reach 0.6 at a 12-month lead (Luo et al., 2005).

Figure 1. Sea surface temperature (SST) climatology based on the HadISST1 observation (a) and ICMv2 simulation (b). The mean simulated SST is obtained from the control run between 1 and 1,000 years, while the observed SST is calculated from 1870 to 2016. The bias between the simulation and observation is shown in (c).
are coupled via the OASIS3 coupler (Valcke, 2013), without flux correction. In the air-sea coupling, six oceanic model variables are delivered to the atmospheric model, and 17 atmospheric model variables including zonal and meridional wind stress over water and sea ice, freshwater and long and short wave flux (Huang et al., 2014) are delivered to the oceanic model via OASIS3. The exchange frequency of the atmospheric and oceanic model is 12 time steps, with 4 hr for each one.

2.2. Observational Data
The monthly sea ice and SST data from HadISST1 (Rayner et al., 2003), from 1981 to 2010, are used as the observations in the initialization scheme and to verify the prediction. HadISST1 has a resolution of 1° latitude × 1° longitude. The statistical relationship between SST and sea ice concentration is used to estimate the SST near the sea ice (Rayner et al., 2003). The surface zonal wind in Reanalysis-2 (Kanamitsu et al., 2002) is used to verify the generated zonal wind in the initialization scheme. The observed subsurface ocean temperature data are from potential temperature in Global Ocean Data Assimilation System (http://www.cpc.ncep.noaa.gov/products/GODAS; Ji et al., 1995; Behringer et al., 1998; Saha et al., 2006). We also used the warm water volume index, defined as the warm water volume above 20 °C isotherm in the tropical area −5°S to 5°N, 120°E to 80°W (McPhaden, 2012), to represent the subsurface oceanic state.

2.3. Model’s Climatology
ICMv2 has been steadily integrated for 1,000 years without flux correction (Liu et al., 2018). Figure 1 shows the annual-mean SST climatology simulated in ICMv2 and the differences from observation (HadISST1). The SST climatology is realistically reproduced in ICMv2, with the bias less than 1 °C in most regions except off the coast of Africa, albeit some common problems in other coupled models, such as MPI-OM/ECHAM5 (Keenlyside et al., 2005), KCM (Park et al., 2009), and SINTEX-F (Luo et al., 2005), also exist here, for example, an excessive cold bias in the equatorial central Pacific, positive bias off the tropical coasts, and negative bias near the eastern coast of Asia and North America (Huang et al., 2014). The apparent bias off the African coast is possibly caused by an imperfect description of coastal upwelling, as in some other CGCMs with similar atmospheric and oceanic components (Park et al., 2009).

ICMv2 also reproduces a realistic seasonal cycle in the central eastern Pacific—the key region for ENSO development and evaluation. The Niño3.4 index, representing the SST variation in the central eastern Pacific, has a very realistic seasonal cycle compared with observations, with the annual cycle peaking in May (Figure 2). The largest bias (about 0.31 °C) appears in August, whereas the biases in other months are less than 0.25 °C. The simulations of ENSO and some other features in ICMv1 and ICMv2 have been shown in detail previously in Huang et al. (2014) and Liu et al. (2018), respectively. ICMv1 and ICMv2 can quite realistically simulate the amplitude, pattern, period, and phase locking of ENSO according to the previous studies (Huang et al., 2014; Liu et al., 2018).

![Figure 2. Average sea surface temperature (SST) of the Niño3.4 region for each month of the 1,000-year control run (red line) and HadISST1 observations (blue line).](http://www.agu.org/journals/AAGU/10.1029/2019MS001620/Figure2.png)
3. Initialization and Experimental Design

3.1. Initialization

An initialization system based on ICMv2 is developed. In the initialization process, the SST in the oceanic model is first nudged strongly toward the observation (HadISST1). Daily SST observations for the hindcast period, 1981–2010, are obtained by applying linear interpolation to the monthly SST observations of HadISST1. These generated SSTs in the oceanic model are used to drive the atmospheric model in ICMv2 for the production of surface fluxes. The surface fluxes from the atmospheric model in turn force the oceanic model to produce the ocean heat content, as in previous studies (Keenlyside et al., 2005; Luo et al., 2005; Morioka et al., 2018). In the oceanic model NEMO 2.3, a negative sea surface feedback parameter $d_Q$ is important for generating the initial values (Madec, 2008):

Figure 3. Time-longitude cross section of sea surface temperature anomalies along the equator (5°S to 5°N, 130°E to 80°W) of the generated initial values ($dqdt0 = 2,300$) in (a) and observation (HadISST1) in (b) during the period 1981–2010.
\[ Q_{ns} = Q_{ns}^o + \frac{dQ}{dT}(T|_{k=1} - SST_{Obs}). \]  

Figure 4. Time-longitude cross section of zonal wind anomalies at 10 m above sea level along the equator (5°S to 5°N, 130°E to 80°W) of the generated initial values (dqdt0 = 2.300) in (a) and observation (Ranalysis-2) in (b) during the period 1981–2010. NCEP = National Centers for Environmental Prediction.
surface sea temperature in the model to make it closer to the observation. When dqdt0 increases, the strength of the negative feedback enhances, which means the SST in the model is getting close to the observation more quickly. When dqdt0 is equal to 2,400, the corresponding relaxation time of a 50-m mixed layer temperature is about 24 hr (Luo et al., 2005).

Figures 3 and 4, respectively, show the SST and zonal wind anomalies produced in the equatorial Pacific Ocean (meridional mean of 5°S to 5°N, from 130°E to 80°W) for the period 1981–2010 with a sea surface feedback parameter of dqdt0 = 2,300 as a demonstration. In Figure 3, the generated SST anomalies in the equatorial Pacific Ocean are in good agreement with the observations from HadISST1, in terms of pattern and amplitude. These initialized SST anomalies successfully describe the seasonal and interannual variability of SST anomalies, including all ENSO signals, during the period 1981–2010. Figure 4 illustrates the zonal wind anomalies produced, which basically reflect both the atmospheric and oceanic conditions. These anomalies (Figure 4a) can successfully describe the structure of “observed” anomalies, represented by the Reanalysis-2 data (Figure 4b), despite an overestimated magnitude. The corresponding ACC of warm water volume index between the model generated initial values for dqdt0 = 2,300 and the observation is 0.8607. In general, the present initialization can provide realistic atmospheric and oceanic initial values in the tropics for ENSO prediction.

3.2. Experimental Design

Experiments were designed to study the influence of the initialization parameter, the SST-nudging strength dqdt0, on the ENSO prediction skill. In the previous studies, the negative feedback coefficient (dqdt0) was usually set at three values, which were 800, 1,200, and 2,400 (e.g., Doi et al., 2016; Luo et al., 2005; Luo et al., 2008; Morioka et al., 2014; Morioka et al., 2018). Based on this, we expanded the range of dqdt0 as wide as possible from 700 to 3,000, and the seven selected dqdt0 values (dqdt0 = 700, 1,300, 1,800, 2,000, 2,300, 2,400, and 3,000) distribute basically uniformly and are enhanced around the most frequently selected 2,400 in previous studies (e.g., Luo et al., 2005; Morioka et al., 2014). In the nudging process, we saved the first to the fifth day values of the month as the initial value of the first day of the month for each dqdt0 value during the period 1981–2010. Specifically, we saved the first to fifth day values at 0 o'clock of the month for dqdt0 = 700, 1,300, and 3,000 as well as the first to fifth day values at 0 o'clock and 12 o'clock for dqdt0 = 1,800, 2,000, 2,300, and 2,400. Each initial value was subjected to a 12-month hindcast experiment. Referring to the definition of forecasting lead time in Luo et al. (2005), the integral length of prediction is the lead time. The dqdt0 experiment groups are named according to the notation SXXXX; for example, S1300 for the group of experiments with initial values generated using dqdt0 = 1,300. We constructed all sets with five nonrepeating members selected from single dqdt0 groups (hereafter referred to as the single initialization parameter ensemble [SIPE] approach) and calculated the average ACC of all five-member SIPE sets across 1- to 12-month lead time to represent the five-member SIPE forecasting level for each dqdt0 (e.g., S2300(5)). The dqdt0 parameters were just selected in the initialization models, which do not influence the dynamics of the model in prediction.

To analyze the influence of the MIPE approach on ENSO prediction skill, we calculated the ensemble prediction skill of these MIPE experiments and compared them with the ensemble prediction skill of experiment sets in which 10 members were selected from single dqdt0 groups. Three sets of SIPE members were selected from dqdt0 = 1,800, 2,000, and 2,300, respectively, and three sets of two-parameter MIPE members were selected from the same groups. These 10-member two-parameter MIPE sets were S1800 and S2000, S1800 and S2300, and S2000 and S2300. We used a Monte Carlo approach (Metropolis & Ulam, 1949) here to generate 20,000 combinations for each two-parameter MIPE set. Specifically, we randomly selected five nonrepeating members from one group and five nonrepeating members from the other group to form a two-parameter 10-member MIPE combination. Then we calculated the average ACC values for these

Figure 5. Anomaly correlation coefficients (ACCs) and root-mean-square errors (RMSEs) of the generated Niño3.4 index values from the nudging process for different dqdt0s during the period 1981–2010.
combinations across 1- to 12-month lead time to represent the forecasting level of each two-parameter MIPE set. Furthermore, on the basis of two-parameter MIPE, we used a Monte Carlo approach (Metropolis & Ulam, 1949) to randomly generate 20,000 ten-member five-parameter MIPE sets. Specifically, we randomly selected three ensemble members from S2000, three members from S2300, and four members from other dqdt0 group (dqdt0 = 1,300, 1,800, and 2,400), obtained 10 members for each MIPE combination and calculated the average ACC between the 20,000 MIPE combinations and observed Nino 3.4 index across 1- to 12-month lead time. Then we counted the proportion of MIPE with larger ACC than the 10-member SIPE.

4. Results
4.1. Influence of SST-Nudging Strength on the Generated Initial Values
Through changing the SST-nudging strength (dqdt0 = 700, 1,300, 1,800, 2,000, 2,300, 2,400, and 3,000), we obtained seven sets of monthly mean initial values during the period 1981–2010. The influence of SST-nudging strength on the generated initial values in the central eastern equatorial Pacific is examined by calculating their respective metrics in the form of the ACC and root-mean-square error (RMSE), with the observations used in the initialization. The larger the ACC and smaller the RMSE, the closer to observation the generated initial values are. We selected the Niño3.4 index to represent the SST anomalies in the central eastern equatorial Pacific. As shown in Figure 5, the ACCs for all selected dqdt0 values are greater than 0.98, consistent with the results in Figure 3, indicating that the initial values generated from ICMv2 are very close to observation in the central eastern Pacific. Apparently, the ACC and RMSE vary with different SST-nudging strengths. In general, the ACC decreases and RMSE increases with the increase in SST-nudging strength from 700 to 2,300. However, the ACC increases as dqdt0 increases from 2,300 to 2,400. This result implies that there is a complex relationship between the SST-nudging strength and the discrepancy between the generated initial values and the observations.

4.2. Prediction of Different Initialization Parameters
The Niño3.4 index prediction skill from a 1- to 12-month lead time is evaluated via ACC (Figure 6). Five-member ensemble forecasts are used to represent the prediction skill of each dqdt0 group. It is quite clear and reasonable that the prediction skill for each dqdt0 group decreases as the lead time increases (Figure 6). The prediction skill shows apparent spread among the different dqdt0 groups, especially at the 6- to 12-month lead times. The spread of ACCs increases along with the increase in lead time. The difference in ACC between dqdt0 = 700 and dqdt0 = 2,300 can reach 0.164 at the 12-month lead time. However, the relationship of the prediction skill among different dqdt0 groups is mixed. The ACC in one dqdt0 group can be greater at certain lead times than the ACC in another dqdt0 group, but smaller at other lead times, which implies the influence of random errors on the prediction skill.

In Figure 6, the smallest and largest ACC for the seven ensemble forecasts appear at dqdt0 = 700 and dqdt0 = 2,300, respectively. The ACC of the ensemble forecast of the dqdt0 = 2,300 group (S2300(5)) can reach 0.78 and 0.648 at a 6- and 12-month lead times, respectively, whereas the ACC of the S700 ensemble forecast is only 0.687 and 0.484 at the same lead times, respectively. Basically, the prediction’s ACC (Figure 6) increases along with the increase of dqdt0 (Figure 6) when the dqdt0 is less than 2,300 but dramatically decreases with the increase of dqdt0 when the dqdt0 is greater than 2,300. The largest ensemble forecast ACC (S2300(5)) does not appear in the group with the initialization values closest to observation, which is the dqdt0 = 700 group (Figure 5). This result indicates that the initialization values closer to “observation” are unable

Figure 6. Anomaly correlation coefficients (ACCs) of Niño3.4 index between the observation and the ensemble mean of the seven designed hindcast experiments of different dqdt0s at 1- to 12-month lead times. The hindcast period is 1981–2010.
to predict an ENSO closer to the same observation. This could be because the observed data sets cannot represent the actual climate condition perfectly; the observed errors vary month by month, and the errors could develop nonlinearly in the prediction. Moreover, the highest ENSO prediction skill associated with dqdt0 = 2,300 differs from the SST-nudging strength in Luo et al. (2005), in which the SST-nudging strength was selected as 2,400 for their model and ensemble forecast.

4.3. MIPE Results

Inspired by the multimodel ensemble mean benefiting from the offset of prediction errors among ensemble members to improve the prediction skill (e.g., Barnston et al., 2017), we performed the MIPE forecasts. As introduced in section 3.2, we conducted three sets of two-parameter MIPE forecasts and compared them with the results of the previous SIPE forecasts. Figure 7 shows the ACCs of the 10-member ensemble of three SIPE sets (S1800(10), S2000(10), S2300(10)), best-performing five-member SIPE set (S2300(5)), and three two-parameter MIPE sets. The three SIPE sets are three best-performing dqdt0 groups in Figure 6: S1800, S2000, and S2300. The three two-parameter MIPE sets are a cross combination of S1800, S2000, and S2300, which are S1800 and S2000, S1800 and S2300, and S2000 and S2300 with 10 ensemble members. From Table 1 and Figure 7, all three of the two-parameter MIPE experiments show higher ENSO prediction skill than the three SIPE experiments before a 10-month lead time, especially at a 5- to 9-month lead time.

We further analyze another set of 10-member MIPE forecasts with members from more dqdt0 groups. From five dqdt0 groups (dqdt0 = 1,300, 1,800, 2,000, 2,300, and 2,400), four members are randomly selected from dqdt0 = 1,300, 1,800, and 2,400, three members from dqdt0 = 2,000, three members from dqdt0 = 2,300, and then 10 members consist of an MIPE combination. A total of 20,000 such kind of MIPE combinations is selected, and their average ACC values across 1- to 12-month lead time are shown in Table 2 along with the five-member SIPE S2300(5) and the 10-member SIPE S2300(10) in Table 1. Although the 10 ensemble members of the MIPE sets are randomly selected from five dqdt0 groups whose prediction skills are spread, and the two SIPE sets have the best prediction skill among the dqdt0 groups, the prediction skill of the MIPE set is apparently higher than those of the SIPE sets at 1- to 10-month lead time. The percentage of 20,000 MIPE combinations greater than S2300(10) is more Table 1

| ACC of Niño3.4 Index at 1- to 12-Month Lead Time Between the Observation and the 10-Member Ensemble Results of Three MIPE Two-Parameter Experiments and Three SIPE Experiments |
|-----------------|----------------|----------------|----------------|----------------|-------|-------|-------|-------|-------|-------|-------|
| Dqdt0           | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11   | 12   |
| S1800, S2000    | 0.986 | 0.939 | 0.898 | 0.866 | 0.829 | 0.796 | 0.776 | 0.766 | 0.751 | 0.721 | 0.680 | 0.634 |
| S1800, S2300    | 0.986 | 0.939 | 0.900 | 0.870 | 0.832 | 0.795 | 0.778 | 0.770 | 0.756 | 0.727 | 0.694 | 0.654 |
| S2000, S2300    | 0.984 | 0.936 | 0.903 | 0.873 | 0.839 | 0.804 | 0.788 | 0.778 | 0.762 | 0.736 | 0.700 | 0.658 |
| S1800(10)       | 0.984 | 0.935 | 0.889 | 0.857 | 0.816 | 0.780 | 0.758 | 0.750 | 0.736 | 0.702 | 0.665 | 0.623 |
| S2000(10)       | 0.979 | 0.928 | 0.894 | 0.859 | 0.825 | 0.791 | 0.774 | 0.761 | 0.742 | 0.714 | 0.671 | 0.625 |
| S2300(10)       | 0.980 | 0.925 | 0.892 | 0.864 | 0.826 | 0.786 | 0.772 | 0.763 | 0.749 | 0.724 | 0.697 | 0.661 |
| S2300(5)        | 0.980 | 0.924 | 0.890 | 0.860 | 0.821 | 0.780 | 0.765 | 0.754 | 0.739 | 0.713 | 0.684 | 0.648 |

Note: The hindcast period is 1981–2010. ACC = anomaly correlation coefficient; MIPE = multiple initialization parameter ensemble; SIPE = single initialization parameter ensemble.
The high skill of the ICMv2 short-term forecast system in predicting ENSO must also be associated with its high-level performance in simulating the climatology in the tropical Pacific (Figure 1), as well as the characteristics of ENSO (Figure 2; Huang et al., 2014; Liu et al., 2018) and its competence in the initialization process as shown in Figures 3–5.

5. Summary and Discussion

In this study we investigated the influence of one key initialization parameter, the SST-nudging strength, on the ENSO prediction skill, based on a CGCM, ICMv2. Different SST-nudging strengths (dqdt0 = 700, 1,300, 1,800, 2,000, 2,300, 2,400, and 3,000) were used to generate a set of initialized values used to forecast ENSO at a 1- to 12-month lead time for the 30-year hindcast period from 1981 to 2010. Furthermore, we conducted a series of ensemble forecasts with ensemble members from the forecasting sets of initial values generated from different SST-nudging strengths, referred to here as the MIPE, and compared them with the prediction skill of the more commonly used SIPE.

The selection of SST-nudging strength in the initialization can apparently affect the prediction skill. However, the ENSO prediction skill does not increase consistently along with the decreased discrepancy between the initialization values and observations, implying an influence of the development of observational errors in the initialization on the prediction skill. When the SST-nudging strength is selected as 2,300, the ACC between the predicted Niño3.4 index in a five-member SIPE forecast and observation can reach 0.78 and 0.648 at a 6- and 12-month lead times, respectively.

We further implemented a 10-member MIPE forecast with members from two different SST-nudging strength groups and compared the prediction skill of the MIPE experiments with that of 10-member SIPE experiments. The ACCs of the two-parameter MIPE forecasts apparently exceed those of the SIPE forecasts at a 1- to 10-month lead time, even the best-performing SIPE (dqdt0 = 2,300), although the members of the MIPE are selected from other relatively low performing dqdt0 groups. Then, we increased the parameter diversity of the MIPE to five under the same 10 ensemble members, and the ENSO prediction skill of the five-parameter MIPE forecasts is significantly higher than that of the SIPE forecast across a 1- to 10-month lead time. The mean ACC of the 20,000 five-parameter MIPE combinations reaches 0.805 at a 6-month lead time and 0.654 at 12-month lead time. This result implies that increasing the parameter diversity in the MIPE could obtain improved prediction skill.

The final prediction skill of the MIPE forecast in the ICMv2 short-term forecast system is quite competitive relative to previous studies (e.g., Barnston & Tippett, 2013; Barnston et al., 2017; Kirtman & Min, 2009; Luo et al., 2005; Merryfield et al., 2013). For example, the ACC of the MIPE forecast here at a 12-month lead time can reach 0.654 for the original monthly SST anomalies, whereas the forecast’s ACC for the period 1982–2001 in Luo et al. (2005) is 0.6. The prediction of ENSO by CFSv2 for the period 1982–2015 only extends to a 9.5-month lead time, and the corresponding ACC is 0.77 (Barnston et al., 2017), whereas the ACC of the MIPE forecast is 0.759 and 0.732 for the original monthly SST anomalies, at a 9- and 10-month lead time, respectively. The ACC in the North American Multimodel Ensemble for the period 1982–2015 is 0.63 and 0.52 at a 9.5 and 11.5-month lead time, respectively, while that for CMC2 is 0.75 and 0.68 (Barnston et al., 2017).

We conducted a series of ensemble forecasts with ensemble members from the forecasting sets of initial values generated from different SST-nudging strengths, referred to here as the MIPE, and compared them with the prediction skill of the more commonly used SIPE.

The selection of SST-nudging strength in the initialization can apparently affect the prediction skill.

However, the ENSO prediction skill does not increase consistently along with the decreased discrepancy between the initialization values and observations, implying an influence of the development of observational errors in the initialization on the prediction skill. When the SST-nudging strength is selected as 2,300, the ACC between the predicted Niño3.4 index in a five-member SIPE forecast and observation can reach 0.78 and 0.648 at a 6- and 12-month lead times, respectively.

We further implemented a 10-member MIPE forecast with members from two different SST-nudging strength groups and compared the prediction skill of the MIPE experiments with that of 10-member SIPE experiments. The ACCs of the two-parameter MIPE forecasts apparently exceed those of the SIPE forecasts at a 1- to 10-month lead time, even the best-performing SIPE (dqdt0 = 2,300), although the members of the MIPE are selected from other relatively low performing dqdt0 groups. Then, we increased the parameter diversity of the MIPE to five under the same 10 ensemble members, and the ENSO prediction skill of the five-parameter MIPE forecasts is significantly higher than that of the SIPE forecast across a 1- to 10-month lead time. The mean ACC of the 20,000 five-parameter MIPE combinations reaches 0.805 at a 6-month lead time and 0.654 at 12-month lead time. This result implies that increasing the parameter diversity in the MIPE could obtain improved prediction skill.

The final prediction skill of the MIPE forecast in the ICMv2 short-term forecast system is quite competitive relative to previous studies (e.g., Barnston & Tippett, 2013; Barnston et al., 2017; Kirtman & Min, 2009; Luo et al., 2005; Merryfield et al., 2013). For example, the ACC of the MIPE forecast here at a 12-month lead time can reach 0.654 for the original monthly SST anomalies, whereas the forecast’s ACC for the period 1982–2001 in Luo et al. (2005) is 0.6. The prediction of ENSO by CFSv2 for the period 1982–2015 only extends to a 9.5-month lead time, and the corresponding ACC is 0.77 (Barnston et al., 2017), whereas the ACC of the MIPE forecast is 0.759 and 0.732 for the original monthly SST anomalies, at a 9- and 10-month lead time, respectively. The ACC in the North American Multimodel Ensemble for the period 1982–2015 is 0.63 and 0.52 at a 9.5 and 11.5-month lead time, respectively, while that for CMC2 is 0.75 and 0.68 (Barnston et al., 2017).

The high skill of the ICMv2 short-term forecast system in predicting ENSO must also be associated with its high-level performance in simulating the climatology in the tropical Pacific (Figure 1), as well as the characteristics of ENSO (Figure 2; Huang et al., 2014; Liu et al., 2018) and its competence in the initialization process as shown in Figures 3–5.
Here, the high-level performance of MIPE forecast is just based on 10 ensemble members, which was designed to compare with the 10-member SIPE forecast. We also analyzed the MIPE prediction results based on 15 and 20 ensemble members (not shown), which are slightly improved relative to the 10-member MIPE. However, the optimization of MIPE could depend on the selection of values and numbers of dqdt0, which is worthy of further investigation in future. In this study, only one initialization parameter—the SST-nudging strength—is discussed. Other parameters contributing to the initialized values could also influence the prediction skill and then be used in the MIPE forecast. One aspect we could also explore is to implement an ensemble of different initialization schemes in the prediction of ENSO, such as the nudging scheme in SINTEX-F (Luo et al., 2005), or simply use the initial values from an assimilation system like in CFSv2 (Saha et al., 2014). Our study provides a new strategy for improving the prediction skill and saving the calculation cost. It is, however, necessary in future studies to optimize the prediction by considering the diversity of initialization parameters in the ensemble forecast, while the multiple model ensemble and the multiple initialization value ensemble have been conventional.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (41722504, 41575088 and 41530426), the Public Science and Technology Research Funds Project of the Ocean (201505013), the Youth Innovation Promotion Association of CAS, and the Fundamental Research Funds for the Central Universities. We would like to thank two reviewers for their detailed and constructive suggestions. The observation data sets HadSST1 (http://hadobs.metoffice.com/hadsto/data/), NCEP-DOE Reanalysis 2 (https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.gaussian.html), and GODAS (https://www.esrl.noaa.gov/psd/data/gridded/data.godas.html) are available in public respectively from Met Office and the NOAA Earth System Research Laboratory’s Physical Sciences Division (PSD). Model outputs are available in public (https://github.com/Sally201907/ICMv2/tree/master/Data). For more details, please contact the corresponding author (huangqing@iap.ac.cn).

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WANG ET AL.

2877
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