Predictability of Two Types of El Niño Assessed Using an Extended Seasonal Prediction System by MIROC

YUKIKO IMADA
Meteorological Research Institute, Japan Meteorological Agency, Ibaraki, Japan

HIROAKI TATEBE
Japan Agency for Marine-Earth Science and Technology, Kanagawa, Japan

MASAYOSHI ISHII
Meteorological Research Institute, Japan Meteorological Agency, Ibaraki, Japan

YOSHIMITSU CHIKAMOTO
International Pacific Research Center, University of Hawai‘i at Mānoa, Honolulu, Hawaii

MASATO MORI, MIKI ARAI, MASAHIRO WATANABE, AND MASAHIDE KIMOTO
Atmosphere and Ocean Research Institute, University of Tokyo, Chiba, Japan

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ABSTRACT

Predictability of El Niño–Southern Oscillation (ENSO) is examined using ensemble hindcasts made with a seasonal prediction system based on the atmosphere and ocean general circulation model, the Model for Interdisciplinary Research on Climate, version 5 (MIROC5). Particular attention is paid to differences in predictive skill in terms of the prediction error for two prominent types of El Niño: the conventional eastern Pacific (EP) El Niño and the central Pacific (CP) El Niño, the latter having a maximum warming around the date line. Although the system adopts ocean anomaly assimilation for the initialization process, it maintains a significant ability to predict ENSO with a lead time of more than half a year. This is partly due to the fact that the system is little affected by the “spring prediction barrier,” because increases in the error have little dependence on the thermocline variability. Composite analyses of each type of El Niño reveal that, compared to EP El Niños, the ability to predict CP El Niños is limited and has a shorter lead time. This is because CP El Niños have relatively small amplitudes, and thus they are more affected by atmospheric noise; this prevents development of oceanic signals that can be used for prediction.

1. Introduction

In the last few decades, dynamical seasonal prediction has progressed considerably thanks to the improved performance of climate models, improved observing and assimilation systems, higher spatial resolution, and better understanding of the tropical oceanic and atmospheric processes underlying the El Niño–Southern Oscillation (ENSO) phenomenon (Wang et al. 2009). The predictability of ENSO is due to oceanic memory and is based on the delayed oscillator or recharge/discharge paradigm (e.g., Neelin et al. 1998), for which the characteristic time scale is several seasons and is thus much longer than in the atmosphere. In addition, nonlinear dynamics and stochastic atmospheric variability are also important factors that influence the irregularity of ENSO. Thus, a dynamical seasonal forecasting system with a comprehensive atmosphere–ocean coupled dynamical system is essential...
general circulation model (AOGCM) with an ensemble approach is now commonly used by most of the major meteorological centers around the world (Barnston et al. 2012). Currently, skillful ENSO prediction is possible for about 6 months in advance (Wang et al. 2009; Jin et al. 2008; Barnston et al. 2012).

Because the memory of the upper ocean is a key element of ENSO predictability, an accurate choice for its initial state is crucial. There are a number of different strategies for initializing the forecast system: from a simple nudging method for sea surface temperature (SST) to more sophisticated optimization methods such as three-dimensional or four-dimensional variational data assimilation (3DVAR or 4DVAR) for ocean temperature and salinity (e.g., Behringer et al. 1998; Lee et al. 2000), univariate or multivariate optimal interpolation (OI; e.g., Yin et al. 2011), or ensemble Kalman filter (EnKF) assimilation for both oceanic and atmospheric variables (e.g., Evensen 1994; Keppenne et al. 2005). Generally, full data assimilation, which assimilates entire components in the observations, is the mainstream of ENSO prediction. One problem in full assimilation is climate drift in the models; that is, models initialized from observed initial states tend to adjust toward their own climatological mean state while producing a forecast. This comes from systematic biases in the mean basic state. To exclude the mean biases, a set of hindcasts covering several decades (which uses a large amount of computational resources) is an indispensable prerequisite for a forecast system with full assimilation. Anomaly assimilation is one of the solutions to the problem of model bias. In anomaly assimilation, only observed anomalies are assimilated, and climatology of the individual model is maintained in order to prevent climate drift during predictions (e.g., Smith et al. 2007; Keenlyside et al. 2008; Pohlmann et al. 2009, Tatebe et al. 2012). Magnusson et al. (2013) compared the full and anomaly initializations implemented in the European Centre for Medium-Range Weather Forecasts (ECMWF) coupled prediction system, and they showed that anomaly initialization has a clear disadvantage in seasonal-scale predictions, compared to full initialization with calibration; however, their results are likely to be model dependent. On the other hand, Zhu et al. (2012) showed insignificant ENSO prediction difference between them when using the Climate Forecast System, version 2 (CFSv2), the current operational climate prediction model at the National Centers for Environmental Predictions (NCEP). They also pointed out the importance of the multiple-ocean analysis ensemble (MAE) initialization in ENSO prediction. Their seasonal forecasts were improved when they used four ocean analyses from the NCEP and ECMWF for the initialization (Zhu et al. 2012, 2013).

Forecast errors depend not only on climate drift but also on the season, and the phase and intensity of the ENSO being predicted (Jin et al. 2008). The so-called “spring prediction barrier” is well known: forecast errors are more pronounced during the boreal spring, when the persistence of the equatorial Pacific SST anomalies also drops (e.g., Latif et al. 1994; Webster 1995). There are various hypotheses for the spring prediction barrier, including the weak air–sea coupling during the boreal spring (e.g., Zebiak and Cane 1987; Battisti 1988) or a phase locking of the ENSO to the annual cycle (Balmaseda et al. 1995; Torrence and Webster 1998). These are related to the annual cycles of the thermocline depth and the intertropical convergence zone (An and Wang 2001). Jin et al. (2008) also pointed out that stronger El Niño or La Niña periods are more predictable than neutral periods, and the growth phase of ENSO is better predicted than the decay phase.

Recent studies have discussed two flavors of El Niño: the eastern Pacific (EP) El Niño and the central Pacific (CP) El Niño (Larkin and Harrison 2005; Ashok et al. 2007; Kao and Yu 2009; Kug et al. 2009). The EP El Niño is the traditional one, in which the maximum warming is in the equatorial eastern Pacific. On the other hand, in the CP El Niño, the maximum SST anomaly is concentrated in the central Pacific. Many global climate anomalies, such as rainfall and temperature in Asia, Australia, and North America (Larkin and Harrison 2005; Ashok et al. 2007; Weng et al. 2007; Wang and Hendon 2007; Lim et al. 2009, Zhang et al. 2011, 2012) and Atlantic hurricanes (Kim et al. 2009), are sensitive to the flavor of the El Niño, and thus it is important to understand the predictability of each type of El Niño.

It is controversial whether the predictabilities of the two types of El Niño are essentially different. Kim et al. (2009) examined the predictability of both events through index-based analyses. They defined the index of an EP event by SST anomalies in the Niño-3 region (5°S–5°N, 150°–90°W) and a CP event by anomalies in the Niño-4 region (5°S–5°N, 160°E–150°W); they then compared the predictability of each index using the ECMWF seasonal prediction system. They found that the Niño-3 (or EP El Niño) predictability shows clear seasonality and diminishes in the spring, whereas the Niño-4 (or CP El Niño) predictability has no obvious spring barrier. They concluded that CP events are more predictable than EP events.

On the other hand, Hendon et al. (2009) reached a contrasting conclusion. They questioned the
appropriateness of using the Niño-4 index for a CP event, because Niño-3 and Niño-4 are mutually dependent. They introduced a new index for CP events that is independent from the Niño-3 index. Using the Australian Bureau of Meteorology’s coupled ocean–atmosphere seasonal forecast model, they showed that an EP El Niño can be predicted as much as a full season with higher skill than a CP event, even though the predictability of the CP event is less affected by the spring barrier. They also found that their model could not maintain the uniqueness of CP and EP El Niños beyond one season as a result of the EP El Niño systematically extending too far west with increasing lead time. Yang and Jiang (2014) used the NCEP climate forecast system to evaluate the skill of the model using Niño-3 and the El Niño Modoki index (EMI) to predict the two types of El Niño events, and they showed that the EMI is more persistent and predictable than Niño-3 during the boreal summer and autumn. In addition to the use of Niño-3 and EMI, Jeong et al. (2012) identified the EP (CP) El Niño event from the first (second) principal component (PC1; PC2) of an empirical orthogonal function (EOF) analysis. They found that the PC1 (EP event) is more predictable than is the PC2 (CP event) when using the coupled climate prediction multimodel ensemble suite of the Asia–Pacific Economic Cooperation (APEC) Climate Center (APCC). They also applied a composite analysis using strong events of each type of El Niño and discussed the spatial differences of the distributions of anomalies. Such divergent views are due to the dependence of the results on the definition of the indices, and they expose the limitations of the index-based approach. Moreover, these papers did not address the ways in which these two types of El Niño differ in the developments in the ocean, and these are crucial to the predictability of these events. In this study, we developed a new one-tiered seasonal prediction system that uses the Model for Interdisciplinary Research on Climate version 5 (MIROC5), an AOGCM initialized by the anomaly assimilation. We also revisit the difference in predictability of the EP and CP El Niños. Instead of conducting an index-based analysis, we focus on the spatial features relating to their predictability. We also consider the processes that cause predictive error, in terms of the physical processes of the development and decay of each type of El Niño. The following section describes our AOGCM and the experimental design used in our hindcast experiments. The skill of our method for predicting the ENSO is discussed in section 3, and the predictability of each flavor of El Niño is addressed in section 4. A brief summary and a discussion are given in section 5.

2. Methodology

a. Model

The coupled AOGCM used in this study is the MIROC5, which was developed by the Atmosphere and Ocean Research Institute (AORI) of The University of Tokyo, National Institute for Environmental Studies, and the Japan Agency for Marine-Earth Science and Technology (Watanabe et al. 2010). The model includes the atmosphere, land, river, sea ice, and ocean. The ocean and atmosphere are coupled but without applying any flux adjustment.

The atmospheric part is based on the primitive equations for a sphere, using a spectral-transform method for horizontal discretization. A vertical hybrid $\sigma-p$ coordinate (cf. Arakawa and Konor 1996) is used with the model top at around 3 hPa. The horizontal resolution is determined by triangular spectral truncation at total wavenumber 85 (T85) with 40 vertical layers. The physical parameterizations incorporate a higher-order turbulence closure, a prognostic cloud scheme, cloud microphysics, and a prognostic scheme for the number concentrations of cloud droplets and ice crystals [see Watanabe et al. (2010) for the individual schemes]. The convection scheme of Chikira and Sugiyama (2010) has been recently developed, and it contributes to an improvement in the reproducibility of ENSO by controlling the efficiency of the entrainment rate in cumuli (Watanabe et al. 2011).

The ocean part is the Center for Climate System Research (CCSR; now AORI) Ocean Component model (COCO: Hasumi 2006) version 4.5. The model is based on the primitive equations with the Boussinesq approximation. The zonal resolution is 1.4°, and the meridional resolution ranges from 0.5° (near the equator) to 1.4° (higher latitudes). There are 49 vertical levels spanning 2.5 m in the top level and 250 m in the bottom level. The model incorporates a sea ice model. See Hasumi (2006) for more information.

b. Experiments

Our seasonal prediction system is a forecasting system based on MIROC5 that allows local air–sea coupling processes. Using this system, we conducted data assimilation and hindcast experiments. In the assimilation experiment, the observed temperature and salinity anomalies in the ocean were incorporated into model anomalies by an incremental analysis update (IAU) scheme (Bloom et al. 1996; Huang et al. 2002) that updated from 1950 and used the representative concentration pathway 4.5 (RCP4.5) climate forcing for solar radiation, volcanism, greenhouse gases, ozone, aerosol, and land-use changes (Tatebe et al. 2012). In the IAU
scheme, the governing equation for temperature and salinity $X$ is written as

$$\frac{DX}{Dt} = F + \text{Dif} + \frac{\alpha}{\tau} \Delta X^\alpha,$$

where $X^\alpha$ is the analysis, $F$ is the surface flux term, and \text{Dif} is the diffusion term, respectively. An analysis interval $\tau$ is 1 day. The variable $\alpha$ is a constant that is set as 0.025. The last term on the right-hand side is the correction term and is held constant during the analysis interval. Further details of IAU are shown in Tatebe et al. (2012). The observed temperature and salinity were obtained from the gridded monthly objective analysis produced by Ishii et al. (2006) and Ishii and Kimoto (2009) who used the latest observational databases [the World Ocean Database (WOD05), World Ocean Atlas (WOA05), and Global Temperature-Salinity Profile Program (GTSSP) provided by the U.S. National Oceanographic Data Center (NODC)] and an SST analysis [Centennial in situ Observation Based Estimates of variability of SST and marine meteorological variables (COBE SST); Ishii et al. (2005); Hirahara et al. (2014)]. Biases from the expendable bathythermographs (XBTs) and mechanical bathythermographs (MBTs) were eliminated in the objective analysis of Ishii and Kimoto (2009). The data were linearly interpolated to each day and to the ocean model grid. The observed anomaly was defined with a reference period between 1961 and 2000. The model climatology was defined by the noninitialized ensemble twentieth-century simulations in which the model was prescribed by historical natural and anthropogenic forcings. The model climatology and the observed anomalies were assimilated into the model.

The hindcast experiments were performed according to the Climate-system Historical Forecast Project (CHFP; http://www.wcrp-climate.org/wgsip/chfp/references/CHFP.pdf) protocol. Initial states are taken from the above ocean data assimilation system, while atmospheric variables are started from the NCEP reanalysis (Kalnay et al. 1996) on each February, May, August, and November from 1979 to present. Here, we analyzed the hindcast outputs initialized from February 1979 to November 2011. Currently, an eight-member ensemble is available that is formed by the lagged average forecast (LAF; Hoffman and Kalnay 1983) method with 12-h intervals. Each ensemble member is run for 12 months.

One of the characteristics of our seasonal forecasting system is that not full variables but only anomalous components inside oceans are assimilated in the initialization process. Because of the implementation of the anomaly data assimilation, our hindcast products showed several unique characteristics as shown later. For verification of our hindcast results, the objective analysis of Ishii and Kimoto (2009) is used as the ocean observation of SST and subsurface temperature unless otherwise specified.

3. ENSO forecast

a. ENSO predictability

First, we examined the ENSO predictability of our seasonal prediction system. ENSO is a dominant seasonal-scale interannual phenomenon that can influence global climate through teleconnection, and it is a good measure of the prediction skill of a seasonal forecasting system. Hindcasted SST anomalies over the Niño-3.4 (5°S–5°N, 170°–120°W) region are compared to the observation in Fig. 2. Hereafter, anomalies are calculated as deviations from monthly climatology from 1979 to 2008. To make assurance double sure, mean biases for each lead month and each ensemble member are also removed for the hindcast anomalies, although the mean biases are little owing to the initialization of the anomaly assimilation (as we will see later). Overall our hindcast represents the observed phases of the ENSO fluctuation, although accuracy of individual events depends on the ENSO phase and the initial condition. To evaluate the accuracy of ENSO prediction, we calculate two scores: a temporal anomaly correlation coefficient (ACC) and a root-mean-square error (RMSE). Figure 2 shows the ACC and RMSE of the Niño-3.4 index between the hindcast and the observation as a function of prediction lead time (solid lines). For comparison, the scores for a persistence forecast, which assumes that the observed monthly mean anomaly for the month prior to the initial time persists unchanged through the forecast period, are also shown with dashed lines in Fig. 2a, and standard deviations (SDs) of the hindcast and the observation are shown in Fig. 2b. The scores calculated from all forecast cases are shown with black lines in Fig. 2. The ACC scores of our hindcast exceed that of the persistence forecast up to a 1-yr lead, indicating that our seasonal forecasting system works reasonably well (Fig. 2a). The performance can also be confirmed from the ACC score of 0.74 at a 6-month lead time and 0.43 at a 1-yr lead time (Fig. 2a). Timing when the RMSE exceeds the SD of the predicted Niño-3.4 index is also a measure of predictability. The timing is around the seventh lead month, indicating that our system retains skill of ENSO prediction for more than half a year (Fig. 2b). Furthermore, an important aspect of an ENSO prediction system is the simulated amplitude of
the ENSO variability. As the prediction progresses, the SD for the hindcast is damped gradually from the observed level in Fig. 2b, indicating that our hindcast underestimates ENSO variability compared to the observed amplitude.

Figures 3a and 3b show the spatial distribution of ACC scores for the SST at the fourth and seventh lead months. For comparison, the ACC distributions for a persistence forecast are also shown with dashed lines in Figs. 3c and 3d. In most of the area, the ACC of the hindcast is larger than the persistence forecast, indicating that MIROC5 can reasonably predict ENSO-related anomalies. As the forecast goes on, the score drops in the midlatitudes because less-persistent atmospheric fluctuations are dominant and mask oceanic signals in those regions. On the other hand, significant ACC scores distribute in the tropical oceans where SST dominates the atmospheric circulation. In addition, high predictability also exists in the basin along the North Pacific subtropical gyre and in the North Atlantic Ocean. In the Pacific Ocean, the high-ACC area corresponds to the region where SST anomalies are associated with ENSO through the so-called atmospheric bridge (Lau and Nath 1996; Alexander et al. 2002), indicating that ENSO predictability is a measure of accuracy of a seasonal-scale forecast.

Figures 3e and 3f show the spatial distribution of RMSE for SST at the fourth and seventh lead months. For comparison, RMSE of the persistence forecast is also shown in Figs. 3g and 3h. In most of the area, the RMSE of the hindcast is smaller than the persistence forecast except for the western equatorial Pacific, indicating that MIROC5 has significant skill in predicting ENSO-related anomalies in the tropical Pacific Ocean. On the other hand, the distinct error in the western equatorial Pacific can be understood from the characteristics of western expansion of the simulated ENSO anomalies due to overly strong air–sea interaction in our model. A cause of such error is discussed in the next section. In contrast to these errors, components of the mean model drift are sufficiently small as shown in Figs. 3i and 3j, providing enough evidence of the advantage of anomaly assimilation.

To evaluate seasonal dependence of the ENSO hindcast skill, we also showed ACC and RMSE for each initial month in Figs. 2a and 2b with colored lines. Previous studies pointed to a drop in skill in boreal spring with recovery in subsequent seasons, which is sometimes called the spring prediction barrier (e.g., Latif et al. 1994; Jin et al. 2008). This seasonality of forecast skill mainly depends on the potential seasonality of SST persistence (Barnston et al. 2012). The ACC and RMSE of the persistence forecasts shown in Fig. 2 tell us that the cases started in November have high potential persistence during the first seven months before the subsequent boreal spring season. Compared to this, the forecasts that start in February and May potentially have lower persistence with a fast drop of skill, which corresponds to the spring prediction barrier. The August cases start with relatively low persistence because of traces of the barrier, but its decrease thereafter is small with approaching boreal autumn and winter even after a
6-month lead time. The multimodel analysis of ENSO prediction skill by Jin et al. (2008) showed that most of the current seasonal prediction systems have the seasonality of forecast skill depending heavily on the potential persistence, although their skill scores are generally better than the persistence forecast. Interestingly, our system shows seasonality that differs from many other seasonal forecasting systems. The spring prediction barrier is relatively weaker in our system compared to the multimodel results of ACC shown in the Fig. 8 of Jin et al. (2008). For example, in the analysis of Jin et al. (2008), the multimodel ACC of the hindcast initialized at 1 August is more than 0.9 at the 6-month lead time, while the multimodel one initialized at 1 February is less than 0.7. In the prediction of the MIROC5, however, the ACC of the hindcast started in August and February is 0.78 and 0.73, respectively. The seasonal difference of the MIROC5’s hindcasts is smaller (lower in August-started cases and higher in February-started cases) than that of the hindcasts of the other AOGCMs. The reason for this feature is discussed in the next section.

**b. Cause of errors**

To depict the process responsible for prediction errors, we compared the distribution of anomalies for the observations and the hindcasts of every lead month regressed onto the observed and the predicted Niño-3.4 index, respectively. In the observations, a typical ENSO pattern is visible with the maximum positive SST anomaly in the eastern tropical Pacific, and there are wind stress anomalies converging into the Niño-3.4 region (Fig. 4a). Figures 4c–e are the same as in Fig. 4a, but for the predicted SST anomalies at lead times of 1, 4, and 7 months. With a 1-month lead time (Fig. 4c), the predicted pattern is similar to the pattern of the observations. As the prediction progresses (Figs. 4d, e), the warmer anomalies in the eastern equatorial region diminish, and the maximum warming shifts westward with the wind stress convergence. Generally, such a monotonic shift is considered to be a typical feature of the drift of a model toward its original climatology, including the systematic model biases. To examine this possibility, we compared the predicted ENSO patterns to the pattern estimated from the noninitialized historical simulations produced by MIROC5 (Fig. 4b). If the westward error were due to model drift, the regressed ENSO pattern of the noninitialized historical simulation should also be distributed more to the west than the observations. In Fig. 4b, however, the warmer anomalies remain in the far eastern equatorial region, and the ENSO pattern is different from the pattern in Figs. 4d and 4e, that is, the predicted westward tendency is not due to model drift but to some other reason.
Fig. 3. (a),(b) Maps of the ACC for the SST anomaly between the observation [the ProjD dataset by Ishii and Kimoto (2009)] and the hindcast results for 4- and 7-month lead times, respectively. The dotted area indicates the 98% significance level. (c),(d) As in (a),(b), but for the ACC between the observation and the persistence forecast. (e),(f) Maps of the RMSEs between the observation and the hindcast for 4- and 7-month lead times, respectively. (g),(h) As in (e),(f), but for the RMSEs between the observation and the persistence forecast. (i),(j) The mean bias of the model drift for 4- and 7-month lead times, respectively.
To understand the origin of the errors, we compared the maps in Fig. 5, which are the same as the maps in Fig. 4 except for the equatorial vertical section of the sea temperature. The contours of the respective mean temperatures from the observations and the model are shown with black lines, and 16° and 24°C are highlighted as references for the thermocline range. In the observations, zonally opposite anomalies appear along the equatorial Pacific thermocline in a mature phase of ENSO (Fig. 5a). This is a typical pattern for ENSO, and it is maintained by the thermocline dynamics, which can be represented as a delayed oscillator (Neelin et al. 1998). A similar structure is also visible in the results of the noninitialized historical experiment (Fig. 5b). In the hindcast for one month of lead time (Fig. 5c), although the broad pattern resembles the observed pattern, the maximum warming or cooling is not along the thermocline but at a shallower depth. This is because the thermocline in the base state of the model is too broad and penetrates deeper into the subsurface ocean.

In the anomaly assimilation, there is an unavoidable gap between an assimilated anomaly and the mean field, because the observed anomalies are assimilated on the model climatology, which includes systematic
model biases. In MIROC5, the simulated thermocline is too broad and is distributed deeply compared with observations (Imada and Kimoto 2006). As the prediction progresses, the gap increases, and the warm anomaly grows near the surface in the western Pacific, separately from the model thermocline. Previous studies have described two types of modes that can give rise to an ENSO event (Neelin et al. 1998; Fedorov and Philander 2000; Burgers and van Oldenborgh 2003; Wang and Picaut 2004): an SST mode resulting from local SST–wind interactions in the central eastern Pacific, and a thermocline mode resulting from remote wind–thermocline feedback in the western Pacific. The SST mode is associated with east to west propagation of SST anomalies and low-amplitude ENSO events with a frequency from two to three years, whereas the thermocline mode has west to east propagation of the subsurface temperature anomalies and large events.

Fig. 5. As in Fig. 4, but for the longitude–depth section of sea temperature anomalies along the equator. For reference, the contours of the respective mean temperatures from the observations and the model are shown with black lines with a 2°C interval, and 16°C and 24°C are highlighted as references for the thermocline range.
with a frequency from four to five years (Guilyardi 2006; Zhu et al. 2011). The SST mode is controlled by anomalous zonal advection of mean temperature gradients, while the thermocline mode is primarily associated with vertical advection of temperature anomalies, caused by the mean upwelling. These key terms are estimated in Fig. 6 (the calculation method has been shown in a number of studies, e.g., Kang et al.
Lag-regression coefficients against a Niño-3.4 index are shown. In an early stage of the hindcast, the vertical advection term predominantly leads SST development in the eastern tropical Pacific (Figs. 6a–c). At the seventh lead month, on the other hand, a contribution of the vertical advection decreases, and the zonal advection increases from the central to the western tropical Pacific, which leads SST development in the western tropical Pacific. In our forecasting system, the feedback from vertical advection is relatively small because of the diffusive thermocline in the model and the gap between the depth of the assimilated ENSO anomalies and the depth of the model’s thermocline, and thus the SST mode controlled by the zonal advection is relatively dominant. This is why, in our ENSO prediction, the equatorial temperature anomalies shift westward near the surface.

The smaller seasonal dependency of our system’s ability to predict ENSO events can be explained by this erroneous process. Figures 7 and 8 show the RMSE of the SST and the equatorial subsurface temperature for

**Fig. 7.** Maps of the RMSE for the SST anomaly from hindcast results with a 5-month lead time. Hindcasts beginning in (a) May and (c) November. (b),(d) As in (a),(b), but for the persistence forecast.

**Fig. 8.** As in Fig. 7, but for the longitude–depth section of ocean temperature along the equator (averaged 2°S–2°N).
the hindcast and the persistence forecast beginning in May and November. In the prediction that is initialized in November, at a time when ENSO anomalies are more persistent and the predictability is higher than during other seasons (Fig. 2), the distribution of the erroneous area of our hindcast is almost the same as that of the persistence forecast (Figs. 7c,d). On the other hand, in the prediction that is initialized in the boreal spring, from the central to eastern tropical Pacific, the RMSE for the hindcast is smaller than that of the persistence forecast (Figs. 7a,b). This indicates that our system (and lots of other dynamical systems) has the largest errors from May but this is also when persistence is the worst forecast. In other words, the model shows the highest skill relative to persistence from May. This comes about from “dynamical memory” of the dynamical model. Note that the large errors in the hindcast for the western equatorial Pacific, as shown in Figs. 7a and 7c, correspond to the westward extension of the prediction errors mentioned above. This westward tendency of the errors is most noticeable during the boreal spring. We will discuss the reason for this below.

The difference between the two seasons is more apparent in the subsurface ocean. The equatorial section of the RMSE for the persistence forecast beginning in November shows that most errors originated along the thermocline (Fig. 8d). In the persistence forecast beginning in May, on the other hand, errors near the surface are separated from the thermocline (Fig. 8b). This can be understood by noting that the ENSO-related anomalies have different structures in the two seasons. Figures 9a and 9c show the same regressed patterns as in Fig. 5, except for the observed temperature anomalies in May and November. In November, when the observed thermocline is at shallower depths in the eastern Pacific, positive anomalies in the subsurface penetrate deep into the thermocline (Fig. 9c). On the other hand, in the first half of the year, when the thermocline sinks in

![Fig. 9](https://example.com/fig9.png)

**Fig. 9.** As in Fig. 5, but at a 1-month lead time for the hindcasts beginning in each month. Hindcasts beginning in (a),(b) May and (c),(d) November. (a),(c) Observation and (b),(d) hindcast.
the eastern Pacific, the large temperature anomalies are distributed near the surface and extend westward away from the thermocline (Fig. 5a). Zebiak and Cane (1987) explained the seasonality of the predictability as being due to the annual cycle of the zonal temperature gradient and the associated variation in the air–sea interaction. ENSO events are more predictable during the boreal summer and autumn, when the thermocline is shallower in the east and the air–sea interaction is relatively strong.

For November initialization, the error in the persistence forecast is reflected in the hindcast errors. In Figs. 7c and 8c, the error distribution for the hindcast is similar to that of persistence forecast, although its amplitude is smaller (the hindcast is better), suggesting that during this season, the predictability is mainly controlled by the persistence of the ocean anomalies. On the other hand, in the hindcast errors from May (Figs. 7a and 8a), we no longer see the large errors near the surface that are visible in the persistence forecast (Figs. 7b and 8b). This can be understood by considering the mean bias of MIROC5. Figures 9b and 9d show the ENSO-related temperature anomalies for May and November with a 1-month lead time. One of the primary weaknesses of MIROC5 is that it produces thermoclines that are too broad and distributed deeply. Early in the prediction from November, assimilated anomalies grow on the thermocline (Fig. 9d), and this results in biases along the thermocline; hence, the prediction from May is insulated from the influence of the systematic thermocline bias. This also means that in the spring barrier season, the feedback from the thermocline is relatively weak, and the feedback from the zonal advection is relatively strong. That is why the westward trend of the errors is larger in the prediction that begins in May (Fig. 7a) than it is in the one that begins in November (Fig. 7c).

In most AOGCMs, a prediction beginning in the boreal spring is more difficult than those beginning in other seasons. Predictability is higher when the thermocline mode is dominant during boreal autumn and winter. In the ENSO prediction of MIROC5, however, the contribution of the vertical advection is underestimated, and so the contribution of the SST mode is relatively stronger even in the boreal autumn and winter. This is why the seasonal difference of the MIROC5’s hindcast is relatively smaller. Overall, the ability of MIROC5 to predict ENSO events is a little below the average of the other official seasonal prediction models (not shown).

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<th>Table 1. ENSO classification [EP El Niño month (EP), CP El Niño month (CP), and La Niña month (La)].</th>
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4. Predictability of the two flavors of El Niño

Understanding the predictability of the CP El Niño is important not only for ENSO studies but also for social issues. This is because the frequency of the CP El Niño has increased in recent decades, and it is likely to increase further until the end of the twenty-first century (Yeh et al. 2009). Here, we examine the difference between the predictabilities of the EP and CP El Niños. Although a few previous studies have examined this difference (Kim et al. 2009; Hendon et al. 2009), they have not determined a specific mechanism that causes this difference. We will focus on the spatial structure and discuss the causes of this difference by considering the discrepancies in each of the processes that cause the anomaly to grow.

a. ENSO classification

We classified each of the months in the hindcast period into one of four categories: EP El Niño months, CP
El Niño months, La Niña months, and other. The EP (CP) El Niño months were defined to be months in which the Niño-3 (Niño-4) SST anomaly exceeds 0.5 K and is larger than the Niño-4 (Niño-3) SST anomaly. These definitions are the same as used by Yeh et al. (2009). The La Niña months were defined to be those in which the Niño-3.4 anomaly is colder than −0.5 K. The classifications for the months of February, May, August, and November are shown in Table 1. In the following composite analyses, we used observations and hindcast outputs of these four months (note these are at intervals of three months). For example, the 4-month-lead hindcasts correspond to the monthly means of May, August, November, and February for those initialized at the beginning of preceding February, May, August, and November, respectively. Similarly, the 7-month-lead hindcasts correspond to the monthly means of August, November, February, and May for those initialized at the beginning of the preceding February, May, August, and November, respectively.

**b. Difference in prediction skill**

Figure 10 shows the ACC skill maps for the SST for each ENSO type in the fourth and seventh lead month. As the lead time increases, the EP El Niño and La Niña show persistent predictability in the eastern tropical Pacific and the basins reached by the remote influence of ENSO, but this is not the case for the western tropical Pacific, where the errors of the westward extension of ENSO anomalies prevent the model from representing anomalies of the opposite sign. On the other hand, the predictability of the CP El Niño is best in the central to western tropical Pacific, and it falls off faster than the predictabilities of either the EP El Niño or La Niña.

Figures 11 and 12 show a composite of the observed and predicted anomalies at the ocean surface and at the subsurface section along the equator, respectively, for the EP and CP El Niños. For the EP El Niños, large positive anomalies exist in the central to eastern tropical Pacific at the beginning of the prediction as well as in the
observations, although the model extends the warm anomalies farther to the west (Fig. 11, left panels). As time progresses, although the eastern warm anomalies decay, because the predicted mean thermocline is too broad, the center of the warming persists along the eastern thermocline (Fig. 12, left panels). In the prediction of the CP El Niño, on the other hand, the predicted anomalies are less persistent, and they decay rapidly with time (Fig. 11, right panels). The surface anomalies are independent of the thermocline for the CP El Niños (Fig. 12, right panels). A key finding in Hendon et al. (2009) was that, for the observed behavior, the pattern correlation between the anomalies for the EP and CP El Niño events is modest, reflecting that the patterns are dissimilar, although their seasonal forecasting model could not maintain the uniqueness of CP and EP El Niños beyond one season. In the same manner, we computed the pattern correlation of the left-hand panels in Fig. 11 with the right-hand panels in the tropical Pacific (30°S–20°N, 120°E–80°W). The pattern
correlation is 0.36 for the observation, 0.60 for a 1-month lead, 0.52 for a 4-month lead, and 0.27 for a 7-month lead, indicating that our forecasting model could maintain the dissimilar spatial patterns between the two types of events.

Figure 13 shows the RMSEs of the temperature for the EP and CP El Niños. The discrepancies in the sources of the errors are apparent. For EP El Niños, the two local maximum RMSEs near the surface originated along the thermocline (Figs. 13a,c). In the prediction of the CP El Niños, on the other hand, the maximum error around the date line is separated from the thermocline (Figs. 13b,d). Kug et al. (2009) showed that vertical advection of anomalies along the thermocline is a key process in the development and decay of the EP El Niño, whereas zonal advection plays an important role in the evolution of the CP El Niño. Contributions of those advection terms for the EP and CP El Niños are estimated in Figs. 14 and 15, respectively, as in Fig. 6. In the composites related to the EP El Niño, the thermocline mode is dominant in the eastern equatorial Pacific at the initial month (Figs. 14a–c). In the seventh lead month, however, the vertical advection term is damped rapidly (Fig. 14f), and instead, a contribution of zonal advection becomes relatively dominant (Fig. 14e), resulting in the westward shift of SST anomalies (Fig. 14d). This is why the RMSE of the EP El Niño is originated along the thermocline (Fig. 13c). On the other hand, in the composites related to the CP El Niño, the vertical advection does not contribute to the development of CP El Niño.
anomalies from the central to the western tropical Pacific, and a main contributor is the zonal advection term both in the first and seventh lead months (Fig. 15). Thus, the RMSE of the CP El Niño is separated from the thermocline (Figs. 13b and 13d). Our results suggested that this difference in the evolution between the two flavors of El Niño is responsible for the distinct error distribution.

In addition, a difference between the signal-to-noise S/N ratios of the EP and CP forms might impact their predictability. We estimated the S/N ratio for each form by defining the signal as the mean amplitude of the ensemble-mean SST anomalies and by defining the noise as the spread of the SST among eight ensemble members (Fig. 16). For reference, we also show the zonal distribution of the average S/N ratio for the atmosphere, which is defined as the ensemble spread of the zonal surface wind from the hindcasts of all months. Across the tropical Pacific, the S/N ratio of CP El Niños is almost half of that of EP El Niños, and this is partially due to the relatively small SST anomalies (signals) of the CP El Niños. The other reason is that the zonal advection feedback, which is a key to the development of a CP El Niño, is closely related to the atmospheric zonal wind, and thus it is more affected by atmospheric noise. The S/N ratio of atmospheric variables is generally smaller than oceanic variables. The S/N ratio of the CP El Niño is similar to that of the surface zonal wind (Fig. 16). This is another reason for the smaller S/N ratio of the CP El Niño. The structures of each S/N ratio well reflect the distribution of prediction skills shown in Fig. 10 in the tropical Pacific.

5. Conclusions

In this paper, we presented a new seasonal forecasting system based on MIROC5, an atmosphere–ocean coupled general circulation model, and we explored its ability to predict ENSO events. Using hindcast results of this forecasting system and factors pertaining to their development, we also examined the difference in predictability between the two flavors of El Niño: the eastern Pacific El Niño and the central Pacific El Niño. In our forecasting system, we adopted an anomaly assimilation method for the initialization procedure. Because the model climatology is equivalent to non-initialized twentieth-century simulations, this system has an advantage in that its forecast experiments are little affected by climate drift; however, it also has a disadvantage in that an initial error could be much larger than in a full assimilation system.

Our forecasting system showed reasonable performance in predicting ENSO events. Interestingly, the forecasting skill of our system is relatively less dependent on the seasonality of persistence and less affected by the spring prediction barrier. By analyzing from the initial month the processes that cause errors, we discovered that it is important to consider the balance of two key processes in the equatorial Pacific Ocean: vertical advection and zonal advection. As a result of the anomaly assimilation method that we adopted, the assimilated large temperature anomalies that are distributed along the thermocline are sometimes misplaced, because there are systematic biases in the climatology of the model, that is, the simulated
thermocline is too broad and penetrates deeper into the ocean compared to observations. Consequently, in MIROC5, the effect of the thermocline mode from vertical advection is relatively small. It is often the case that a model’s prediction skill is better when the thermocline feedback is stronger and worse when the thermocline feedback is weaker. This connects to the cause of the seasonal dependency of the predictability of ENSO events. In MIROC5, however, the thermocline feedback is too weak throughout the year. This is why the seasonal dependency of the prediction skill is relatively small in MIROC5.

Although there are some discrepancies in the balance of the advective feedback seen in the observations and
that seen in MIROC5, our hindcast can successfully distinguish between the two flavors of El Niño: development of EP El Niños is driven by vertical advection and that of CP El Niños is driven by zonal advection. Focusing on the spatial features of the error with each type of El Niño, we determined that the CP El Niño is relatively difficult to predict compared to the EP El Niño, because the signal-to-noise ratio is smaller when the CP El Niño is developing; this is because its amplitude is relatively small, and also it is more affected by atmospheric noise.

There is much room for improvement in the initialization process and in the model itself. We are currently working on an upgraded assimilation system. We also note that several previous studies have shown that multimodel analysis improves seasonal prediction skill.
(e.g., Jin et al. 2008), and so we intend to apply our approach to the multimodel outputs and will present the results in a future paper.

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