Deficiencies and possibilities for long-lead coupled climate prediction of the Western North Pacific-East Asian summer monsoon

Sun-Seon Lee · June-Yi Lee · Kyung-Ja Ha · Bin Wang · Jae Kyung E. Schemm

Received: 4 August 2009 / Accepted: 28 April 2010 / Published online: 8 June 2010 © Springer-Verlag 2010

Abstract Long-lead prediction of waxing and waning of the Western North Pacific (WNP)-East Asian (EA) summer monsoon (WNP-EASM) precipitation is a major challenge in seasonal time-scale climate prediction. In this study, deficiencies and potential for predicting the WNP-EASM precipitation and circulation one or two seasons ahead were examined using retrospective forecast data for the 26-year period of 1981–2006 from two operational couple models which are the National Centers for Environmental Prediction (NCEP) Climate Forecast System (CFS) and the Bureau of Meteorology Research Center (BMRC) Predictive Ocean–Atmosphere Model for Australia (POAMA). While both coupled models have difficulty in predicting summer mean precipitation anomalies over the region of interest, even for a 0-month lead forecast, they are capable of predicting zonal wind anomalies at 850 hPa several months ahead and, consequently, satisfactorily predict summer monsoon circulation indices for the EA region (EASMI) and for the WNP region (WNPSMI). It should be noted that the two models’ multi-model ensemble (MME) reaches 0.40 of the correlation skill for the EASMI with a January initial condition and 0.75 for the WNPSMI with a February initial condition. Further analysis indicates that prediction reliability of the EASMI is related not only to the preceding El Niño and Southern Oscillation (ENSO) but also to simultaneous local SST variability. On other hand, better prediction of the WNPSMI is accompanied by a more realistic simulation of lead–lag relationship between the index and ENSO. It should also be noted that current coupled models have difficulty in capturing the inter-annual variability component of the WNP-EASM system which is not correlated with typical ENSO variability. To improve the long-lead seasonal prediction of the WNP-EASM precipitation, a statistical postprocessing was developed based on the multiple linear regression method. The method utilizes the MME prediction of the EASMI and WNPSMI as predictors. It is shown that the statistical postprocessing is able to improve forecast skill for the summer mean precipitation over most of the WNP-EASM region at all forecast leads. It is noteworthy that the MME prediction, after applying statistical post-processing, shows the best anomaly pattern correlation skill for the EASM precipitation at a 4-month lead (February initial condition) and for the WNPSMI precipitation at a 5-month lead (January initial condition), indicating its potential for improving long-lead prediction of the monsoon precipitation.

Keywords Long-lead coupled climate prediction · Multi-model ensemble · Western North Pacific-East Asian monsoon · East Asian summer monsoon index · Western North Pacific summer monsoon index · Climate Forecast System · Predictive Ocean–Atmosphere Model for Australia · Statistical postprocessing
1 Introduction

Seasonal climate prediction of the Asian summer monsoon precipitation still remains limited, in spite of the fact that state-of-the-art climate prediction models have been improved significantly and verified to be a useful forecast skill for the prediction of long-lead El Niño and Southern Oscillation (ENSO) prediction up to 6 months and beyond (Wang et al. 2007, 2008a, 2009). It has been revealed, however, that the models have difficulties in simulating monsoon mean climatology over Asia, particularly over the East Asian summer monsoon (EASM) region but also have deficiencies in predicting the waxing and waning of summer mean precipitation anomalies (Kang et al. 2002; Kang and Shukla 2006; Wang et al. 2004, 2008a, 2009; Yang et al. 2008; Liang et al. 2009, Lee et al. 2010; and many others). Using 14 climate prediction models, Wang et al. (2009) reported that the use of a 1-month lead multi-model ensemble (MME) prediction is not useful in predicting summer mean precipitation over the region of interest, although climate models realistically predicted the ENSO and associated large-scale circulation in the upper and lower levels. Lee et al. (2010) showed that the deficiencies in predicting seasonal precipitation anomalies over the Asian monsoon region are related to the systematic bias of simulating the monsoon mean state in coupled models.

The coupled climate predictability arises from “slow” coupled dynamics between the ocean, atmosphere and land, and “initial memories” in the ocean and land surfaces (Wang et al. 2009). Since the current coupled models have difficulty in representing realistic land-surface process and in adopting suitable land initialization, atmospheric seasonal climate predictability over the Asian monsoon region mainly arises from atmospheric teleconnection associated with ENSO forcing and monsoon–ocean interactions in the Indian Ocean and Western North Pacific (WNP), given “initial memories” in the ocean (Wang et al. 2008a, 2009; Yang et al. 2008). Using 10 coupled models, Wang et al. (2008a) showed that the state-of-art coupled models can be successfully used to predict the first two dominant modes of interannual variability of the Asian-Australian monsoon (A-AM) rainfall related with ENSO 1 month ahead. The National Centers for Environmental Prediction (NCEP) Climate Forecast System (CFS) has been confirmed to have long-lead predictability for the first two modes of A-AM rainfall up to 6 months, the origin of which is ENSO predictability (Wang et al. 2008a) and the capability of predicting the most dominant mode of the Asian summer monsoon precipitation associated with ENSO development several months in advance (Yang et al. 2008; Liang et al. 2009).

Although the first two dominant modes of A-AM rainfall variability are predictable several months ahead when the current coupled models are used, the reliability of the forecast for total interannual variability is still low especially over the EASM region. Figure 1b of Wang et al. (2007) shows that forecasting skill for summer mean precipitation over most of the Asian monsoon region is almost zero in the case of 1-month lead seasonal MME prediction using the same 10 coupled models as those used by Wang et al. (2008a). This low skill can be mainly attributed to the intrinsic (unpredictable) variability of the Asian monsoon system (Kumar and Hoerling 1995; Rowell 1998; Kang et al. 2004; Kang and Shukla 2006; Kumar et al. 2007), systematic anomaly bias in predictable variability (Feddersen et al. 1999; Kang et al. 2004; Kang and Shukla 2006), and a lack of land-surface initialization (Koster and Suarez 2003).

In this study, the deficiencies and possibilities for long-lead coupled prediction are further investigated, with a particular focus on the WNP-EASM precipitation and low-level circulation, using retrospective forecasts for the 26-year period of 1981–2006 obtained from two operational climate forecast models: NCEP CFS and Bureau of Meteorology Research Center (BMRC) Predictive Ocean–Atmosphere Model for Australia (POAMA). The retrospective forecasts of those coupled models are well suited to assessing long-lead coupled predictability, since they were initiated monthly and integrated for 9 months. The issues to be addressed in this study include: (1) an assessment of the long-lead climate prediction of precipitation and low-level circulation over the WNP-EAM region in coupled models, (2) an examination of the forecasting skill and sources of errors in the prediction, and (3) attempts to improve long-lead climate prediction skill using statistical postprocessing.

Section 2 describes the coupled models and their retrospective forecast data, observed data, and methods used for forecast evaluation. The current status of long-lead coupled climate prediction for the June–July–August (JJA) precipitation and low-level atmospheric circulation is investigated in Sect. 3. In Sect. 4, we tentatively identify the source of seasonal predictability and discuss the limitations of the coupled model for the long-lead prediction of the WNP-EAM system. Section 5 discusses possible approaches for improving the long-lead prediction of the WNP-EAM precipitation using predictable information and statistical postprocessing. Lastly, the findings of the study are summarized in Sect. 6.

2 Data and evaluation methods

2.1 Description of models and their retrospective forecast

The NCEP CFS (Saha et al. 2006) and BMRC POAMA (Wang et al. 2008b) are fully coupled ocean–land–atmosphere dynamical seasonal prediction systems for
operational use and generated a retrospective forecast for the common period of 1981–2006 initiated every month with an integration time of 9 months. Both seasonal prediction systems have their own ocean data assimilation (ODA) scheme for ocean initialization, but they use different schemes for atmospheric initialization.

The atmospheric and oceanic components of CFS are the NCEP atmospheric Global Forecast System (GFS) model (Moorthi et al. 2001) and the Geophysical Fluid Dynamics Laboratory (GFDL) Modular Ocean Model version 3 (MOM3) (Pacanowski and Griffies 1998), respectively. The components have 15 initial atmospheric conditions which have different starting dates. The first (second) set of 5 initial atmospheric states from 9th to 13th (from 19th to 23rd) used the same pentad ocean initial conditions as the 11th (21th). The last set of five initial atmospheric states include the second-to-last day of the month, the last day of the month, and the first, second, and third days of the next month. Since the first 5 members started to integrate 20-days earlier than the forecast target month, we tested the sensitivity in order to choose the number of ensemble members required for obtaining an ensemble mean using all 15 members, the latest 10 members, and the latest 5 members. The findings show that, taking into account JJA precipitation and the 850 hPa zonal wind over Asia and the WNP, increasing the number of ensemble members from 5 to 15 had little effect on improving or degrading seasonal climate forecast skill. Thus, all 15 members were used for calculating ensemble mean. As a matter of convenience, we will refer forecast starting date of the latest three members to the initial conditions. For example, the CFS ensemble-mean forecast with the May initial condition actually includes forecast members initiated from the 9th to 13th, 19th to 23rd and 29th to 30th of April and the 1st to 3rd of May.

The POAMA version 1.5 system used in this study includes the Australian Community Ocean Model version 2 (ACOM2) and the Bureau of Meteorology Research Centre Atmospheric Model version 3 (BAM3) (Alves et al. 2003). Its retrospective forecast has 10 ensemble simulations that are initiated on the first day of every month with different initial conditions from an Atmosphere–Land Initialization (ALI) scheme and the same ocean initial conditions from the ODA system. The ensemble mean for the 10 members is used to assess the seasonal prediction skills of POAMA.

The forecast target season of this study is JJA, i.e., the boreal summer season. Because, in both models, the retrospective forecast is initiated every month with an integration of 9 months, forecast skill can be evaluated from the 6-month lead forecast with previous December initial condition to 0-month lead forecast with June initial conditions. A simple composite (equal weight) was used to prepare the MME.

2.2 Observation

The observation data used in this study for verification are the Climate Prediction Center merged analysis of precipitation (CMAP) (Xie and Arkin 1997), zonal and meridional winds at 850 hPa from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis I (Kalnay et al. 1996), and the sea surface temperature (SST) from the Hadley Center Global Sea-Ice and Sea Surface Temperature (HadISST) data set (Rayner et al. 2003). All observed and predicted data were interpolated to a common resolution of 2.5° longitude by 2.5° latitude before verification.

2.3 Forecast quality measures

The forecast quality measures used include the temporal correlation coefficient (TCC) skill and the anomaly pattern correlation coefficient (PCC) skill. The TCC was obtained from correlation coefficients between observation and prediction for the 26 years of 1981–2006. The PCC skill measures the spatial correlation coefficients between the observed and predicted anomalies over the area of interest (Wang et al. 2004). For convenience of comparison, the time-averaged anomaly PCC was separately calculated over the EAM (100°E–140°E, 20°N–40°N) and WNPM (105°E–160°E, 10°N–22.5°N) regions for the 26-year period. To make unbiased estimates of the mean PCC, we first averaged quadratic measures, such as variance and covariance, and then calculated the time-averaged PCC.

3 Current status of the WNP-EAM prediction

3.1 JJA precipitation and 850 hPa zonal wind

The current status of long-lead seasonal predictions of the WNP-EASM system was investigated using retrospective forecast data from the CFS and POAMA models for the 26-year period of 1981–2006. We evaluated the performance of the two coupled models and their simple MME for predicting the JJA precipitation and 850 hPa zonal wind anomalies with a forecast lead time of up to 6 months over the WNP-EASM region in terms of the TCC and PCC skills.

Figure 1 shows the spatial distribution of the TCC skill for the MME prediction of JJA precipitation anomalies with initial conditions from the previous December to June, respectively. As previous studies have indicated, the current coupled models have no forecast skill for predicting
JJA precipitation over most of Asian continental region at all forecast leads. The TCC skill is very low regardless of forecast lead month. On the other hand, the TCC skill over the WNPSM region is relatively high and increases with decreasing forecast lead time. In particular, some oceanic regions are highly predictable even at a 5-month forecast lead. It is more difficult to predict precipitation over the South China Sea than over the WNP.

The forecast skills over the EASM and WNPSM regions are summarized in Fig. 2 in terms of the 26-year mean PCC skill for JJA precipitation as a function of the initial month of the forecast, obtained from the CFS, POAMA, and their simple MME prediction, respectively. For the case of the EASM precipitation, two coupled models and their MME show very low PCC skills which are sensitive to the initial month. On the other hand, WNPSM precipitation is more accurately predicted and is less sensitive to the initial month. It should be noted that, when the number of models being used for MME is small, the MME approach does not guarantee improved forecast skills. When the forecast skills of the two coupled models are very different from each other or insignificant, the MME skill is not particularly better than the best model skill, as shown in Fig. 2a. The EASM forecasts using January and April initial conditions are such a case. The MME shows the best PCC skill of 0.25 over the EASM and 0.37 over the

Fig. 1 Temporal correlation skill for MME prediction of JJA precipitation obtained from CFS and POAMA initiated from a December (6-month lead), b January, c February, d March, e April, f May, and g June (0-month lead) for 26 years of 1981–2006. The dotted contour represents statistical significance of the correlation coefficients at 0.05 confidence level. Red and blue rectangles indicate the EASM and WNPSM regions, respectively.
WNPSM region at a 0-month forecast lead when both coupled models have relatively good and comparable skills.

Different from the low performance of the coupled models on JJA precipitation anomalies, atmospheric circulation anomalies were found to be predicted accurately, even 6 months ahead over the WNP-EASM region. As shown in Fig. 3, the MME predicts JJA zonal wind anomalies at 850 hPa better than precipitation over continental areas as well as oceanic monsoon regions at all forecast leads. It is interesting to note that the TCC skill for zonal wind over the EASM region maintains a similar level at all forecast leads, while the skill over the WNPSM and Indian monsoon (IM) regions gradually increases with decreasing forecast lead time.

3.2 Monsoon indices

Given the fact that the current coupled models are skillful for predicting JJA zonal wind anomalies at 850 hPa two seasons ahead in the case of the WNP-EASM region, we also investigated the performance of the coupled models on predicting dynamical monsoon circulation indices over that region. It has previously been demonstrated that some of the dynamical monsoon indices are capable of representing interannual variations in the regional summer monsoon system (e.g. Webster and Yang 1992; Wang and Fan 1999; Lau et al. 2000; Huang 2003; Ha et al. 2005).

The monsoon indices used in this study are the WNP summer monsoon index (WNPSMI) and the EA summer monsoon index (EASMI). The WNPSMI is defined by differences between the 850 hPa zonal wind averaged over the southern part of the WNP region (100°E–130°E, 5°N–15°N) and that over the northern part (110°E–140°E, 20°N–30°N) (Wang and Fan 1999; Wang et al. 2001). The EASMI is defined by the intensity of zonal and meridional wind speed at 850 hPa averaged over the EAM region (127.5°E–147.5°E, 32.5°N–37.5°N) (Ha et al. 2005). Although the EASMI was designed to measure the interannual variability of Changma in Korea, we found that it represents, to some extent, the interannual variability in the EASM including Mai-yu in China and Baiu in Japan.

While the domain for defining the WNPSMI in the CFS and POAMA prediction is same as the observation, the domain for the EASMI prediction is different from the observed values. That is because the JJA low-level wind speed over the EASMI region was poorly predicted by both coupled models, even in the case of a 0-month forecast lead (not shown). The EASMI in CFS and POAMA was calculated by averaging the wind speed on specific points where the correlation coefficients between predicted JJA low-level wind speed over the EA region (120°E–147.5°E, 20°N–40°N) and the observed EASMI were significant at the 90% confidence level. To avoid problems associated with overfitting, the correlation coefficients were obtained in cross-validated manner. Consequently, the domain used for producing the EASMI in coupled models is different with initial conditions and each year.

Figure 4 shows the time series for the EASMI and WNPSMI anomaly, respectively, obtained from observation and simple MME prediction with forecast lead times of up to 6 (preceding December initial condition) from 0-months (June initial condition). Each time series was normalized by its own standard deviation. The findings show that MME is capable of predicting the EASMI and WNPSMI. In particular, some strong years which have anomalies of more than one standard deviation are relatively accurately predicted several months ahead, such as 1983, 1997, and 2001 for the WNPSMI. It should be noted that the EASMI and WNPSMI are negatively correlated in relation to ENSO. The EASMI is positively correlated with the preceding DJF NINO 3.4 SST while the WNPSMI is negatively correlated with it. Since the coupled models overestimate the positive relationship between the EASMI and NINO 3.4 SST, a conspicuous forecast error was found when the observed relationship is weakly negative such as in 1983 and 1999. This issue will be revisited in the next section.
The TCC skills for predicting monsoon indices obtained from the CFS, POAMA, and their MME are summarized as a function of forecast lead month in Fig. 5. The two coupled models and their MME predict the two monsoon indices relatively accurately. In particular, the WNPSMI is more predictable than the EASMI. The MME reaches a correlation skill of 0.40 for the EASMI with January initial condition and 0.75 for the WNPSMI with February initial condition, indicating the possibility for the long-lead prediction of the WNP-EASM system.

4 Factors in determining forecast quality

Previous studies have indicated that the climate predictability of the WNP-EASM system on a seasonal time scale mainly arises from the atmospheric teleconnection associated with ENSO variability and interactions with the Indian Ocean and WNP in current climate models (Wang et al. 2007, 2008a, 2009; Yang et al. 2008; Liang et al. 2009). It has been demonstrated that major factors in restricting seasonal climate predictability include intrinsic (noise) variability (Kumar and Hoerling 1995; Rowell 1998; Kang et al. 2004; Kang and Shukla 2006; Kumar et al. 2007), climatological (systematic) bias (Sperber and Palmer 1996; Gadjil and Sajani 1998; Sperber et al. 2000; Lee et al. 2010), anomalous systematic errors associated with ENSO variability (Feddersen et al. 1999; Kang et al. 2004; Kang and Shukla 2006), and problematic land–surface process and land initialization (Koster and Suarez 2003). In this section, the major factors in determining forecast skill and causes of forecast error for the WNP-EASM system are
examined for in the current coupled models, with particular emphasis on the forecast quality for simultaneous SST, the feasibility of reproducing ENSO teleconnection, anomalous errors associated with ENSO variability, and potential predictability.

4.1 Forecast quality for JJA SST anomaly

As mentioned in the first part of Sect. 4, SST variability over the Indo-Pacific Ocean plays a crucial role in determining the interannual variability of the WNP-EAM system. Therefore, the forecast quality for JJA SST anomalies over the region should be considered as a major factor in determining the forecast quality for the monsoon system in current coupled models. Figure 6 shows the anomaly PCC skill for JJA SST predicted by the CFS, POAMA, and their MME over the Central and Eastern Pacific, Indian Ocean, EASM region and WNPSM region, respectively, as a function of initial forecast month. The forecast skill for JJA SST increases gradually with decreasing forecast lead time over the Central and Eastern Pacific and the Indian Ocean, but the short-lead forecast is not always better than the long-lead one over the EASM and WNPSM regions. It should be noted that CFS and POAMA are capable of predicting JJA SST anomalies over the tropical Pacific 6-months ahead, but difficulties are encountered in predicting SST anomalies over the Indian Ocean and the EASM region.

Two issues arise from the results shown in Figs. 5 and 6. First, the coupled model’s success in the EASMI and WNPSMI prediction with January and February initial conditions may not be related to the forecast quality of the simultaneous SST over the tropical Pacific and Indian

Fig. 4 Time series of the normalized JJA a EASMI and b WNPSMI in observation and MME prediction with different forecast initial month. A parenthesized values indicate forecast lead month.

Fig. 5 Temporal correlation skill for prediction of JJA a EASMI and b WNPSMI as a function of forecast lead time obtained from CFS, POAMA, and MME.
Ocean, which is characterized by a gradual increase in skill with decreasing forecast lead time. Second, the forecast skill for the EASMI appears to be more related to the forecast quality of the local SST than that for the WNPSMI. The forecast skills for CFS and POAMA prediction for SST over the EASM region (Fig. 6c) behaves similarly to the skill for the EASMI (Fig. 5a), indicating the better prediction of the EASM circulation is likely linked to the better prediction of local SST over the region. This is consistent with findings reported by Huang et al. (2007) in which the seasonal and interannual variability of SST over the EA coastal regions affect the strength of the EASM, especially after the mid-1970s in their regional climate model. We further investigated the relationship between JJA local SST and the EASMI in terms of observation and prediction. The observed EASMI has a negative relationship with SST in the vicinity of Korea, whereas a significant positive correlation is evident over the East China Sea.

In both models, the negative relationship around the Korean Peninsula tends to be overestimated and the positive correlation over the East China Sea is slightly underestimated. Nonetheless, CFS (POAMA) has the best skill in predicting the EASMI as well as the local SST-EASMI relationship with January (February) initial condition (not shown).

4.2 Time-lagged ENSO teleconnection

The previous section indicates that the forecast skill for simultaneous SST variations over the Central and Eastern Pacific is not a crucial factor in determining the forecast skill for the WNP-EASM circulation in the current coupled models. Since ENSO affects the WNP-EASM system with a time lag (Wang et al. 2000, 2001), it is a matter of great importance for the coupled models to simulate realistic lead–lag relationships between ENSO and the WNP-EASM system. In particular, a relatively high skill for JJA precipitation over the monsoon region has been reported in current climate prediction models in ENSO decaying summers (Wang et al. 2009). Thus, we investigated the lead–lag relationship between summer monsoon indices and the monthly NINO 3.4 SST index in observation and prediction with different initial months.

Figure 7 indicates that the observed EASMI (WNPSMI) has a significant positive (negative) correlation with the NINO 3.4 SST index in the preceding winter and early spring. The maximum lag-correlation coefficient is 0.40 for the EASMI against the preceding December and April NINO 3.4 index, and −0.56 for the WNPSMI against the preceding December and January NINO 3.4 index. While the EASMI has no relationship with the monthly NINO 3.4 index on August and afterward, the WNPSMI has a significant simultaneous and lead relationship with the NINO 3.4 index with a maximum correlation coefficient of 0.55 against the October NINO 3.4 index.

The CFS and POAMA are capable to capture, to some extent, the observed lead–lag relationship with ENSO for both indices but they tend to exaggerate it, especially in cases of long-lead predictions. In particular, the ENSO strongly modulates the EASM circulation in both coupled models and the lead–lag relationship becomes more realistic with decreasing forecast lead time. In terms of the WNPSM circulation, the CFS better simulates the lead–lag relationship than the POAMA at most forecast lead times, which is likely related to the better prediction of the WNPSMI (Fig. 5b). The CFS shows the most realistic lead–lag relationship (blue solid line in Fig. 7b) and the best skill for the WNPSMI (Fig. 5b) with March initial condition. On the other hand, the POAMA has the most realistic relationship and the best skill for WNPSMI at a 0-month lead.

![Fig. 6](same as Fig. 2 except for JJA SST anomaly over a the Central and Eastern Pacific (160°E–240°E, 20°S–20°N), b the Indian Ocean (40°E–120°E, 20°S–20°N), c the EASM region (100°E–140°E, 20°N–40°N) and d the WNPSM region (105°E–160°E, 10°N–22.5°N)](https://example.com/fig6.png)
Since the preceding ENSO variability plays a major role in the EASM circulation in long-lead predictions for both coupled models in Fig. 7, we further investigated the spatial distribution of SST, which is related to the EASMI variability in observation and prediction. Figure 8 describes the TCC between the EASMI and monthly SST in January and June, respectively, in observation and prediction with January initial condition. The January initial condition was used because the CFS shows the best skill with that initial condition. In observation, the EASMI has a significant relationship with SST over the Indian Ocean and mid tropical Pacific with a maximum correlation coefficient of 0.50. The spatial distribution of TCC over the tropical Pacific resembles the El Niño Modoki pattern (Ashok et al. 2007; Weng et al. 2007) rather than typical ENSO pattern. On other hand, the predicted patterns in both CFS and POAMA are almost identical to the typical ENSO SST mode with a maximum correlation of 0.80. Although the ENSO is a major source in predicting seasonal climate systems, the conspicuous impact of the typical ENSO mode on the EASM circulation may limit the predictability of the circulation in the current coupled models. Different from the EASMI, the TCC distribution between the WNPSMI and SST is similar to a typical ENSO SST mode in both observation and prediction (not shown).

In summary, typical ENSO variability is the major predictability source with time lead for the WNPSMI but not for the EASMI. The better simulation of the leading relationship of ENSO against the WNPSMI is related to the better prediction for the index. On other hand, the prevailing role of the typical ENSO variability on the EASMI in coupled models constitutes a limiting factor for the long-lead predictability for the index. Considering the moderate correlation coefficient between the EASMI and SST over the Central Pacific and Indian Ocean in observation (Fig. 8), further study will be needed to identify other important predictability sources of the EASMI and ways to reproduce them in coupled models.

4.3 Potential predictability

The intrinsic variability of atmospheric circulation due to its chaotic nature inherently limits seasonal climate predictability, especially for extratropical climates. Since
signal variance is hardly separated from noise (or internal) variance in observation, dynamical ensemble simulation has been used to assess the potential for predicting seasonal climate prediction (Kumar and Hoerling 1995; Rowell 1998; Kang et al. 2004; Kang and Shukla 2006; Kumar et al. 2007). Thus, the estimated potential predictability of seasonal climate is strongly dependent on the dynamical model used.

The total atmospheric variance \( \sigma^2_{\text{TOT}} \) is divided into signal \( \sigma^2_{\text{SST}} \) and noise variances \( \sigma^2_{\text{INR}} \) (Rowell 1998). Noise (internal) variance can be expressed as

\[
\sigma^2_{\text{INR}} = \frac{1}{N(n-1)} \sum_{i=1}^{N} \sum_{j=1}^{n} (x_{ij} - \bar{x}_i)^2
\]

where \( x \) is a variable such as precipitation or wind, \( i \) indicates the individual year, \( N \) is total number of years, \( j \) is the ensemble member, and \( n \) is the number of total ensemble members. \( \bar{x}_i \) is the ensemble mean. Signal (external) variance is obtained from the mean square of the deviation of each year’s ensemble mean from the climatological mean and with a consideration of bias correction.

\[
\sigma^2_{\text{SST}} = \sigma^2_{\text{EN}} - \frac{1}{n} \sigma^2_{\text{INR}}
\]

\[
\sigma^2_{\text{EN}} = \frac{1}{N-1} \sum_{i=1}^{N} (\bar{x}_i - \bar{x})^2
\]

\[
\bar{x} = \frac{1}{Nh} \sum_{i=1}^{N} \sum_{j=1}^{n} x_{ij}
\]

Using the ratio of signal variance to noise variance, Kang and Shukla (2006) expressed the theoretical limit of seasonal prediction correlation skill as

\[
R_{\text{Limit}} = \sqrt{\frac{\rho}{\rho + 1}}
\]

where \( \rho \) is the signal-to-noise ratio (signal variance/noise variance). They showed that the theoretical limit of correlation skill is very similar to the perfect model correlation which is estimated by considering one of the ensemble members as observation.

The theoretical limit of the correlation skill for JJA 850 hPa zonal wind was examined using CFS and POAMA predictions. The theoretical limit generally increases with decreasing forecast lead time, because of error growth. In certain cases, however, long-lead predictions show a comparable or better potential predictability than short-lead predictions. Figure 9 shows the theoretical limit using the CFS and POAMA prediction with January and June initial conditions, respectively. There are two interesting features in the results, when POAMA is used. First, the JJA zonal wind over the EASM region is potentially as predictable as that over the subtropics. However, regarding JJA precipitation, the EASM region is much less predictable than the WNPSM region (not shown). Second, JJA zonal wind is more potentially predictable with January initial condition than June initial condition over the some parts of the EASM region. POAMA can predict potentially more than 50% (correlation coefficient of 0.70) of the total variation of the 850 hPa zonal wind over the center of the EASM region five months ahead.

JJA zonal wind at 850 hPa is more potentially predictable by POAMA than CFS for initial conditions of both January and June. This is because that zonal wind responds more strongly to SST variations in POAMA and, as a result, the ensemble-mean variance of the zonal wind is larger than the inter-ensemble variance. Since the CFS has
3 different SST initial conditions with 15 different starting days for each forecast lead, we further checked the theoretical limit of correlation skill for each ensemble group, which consists of 5 ensemble simulations. The findings show that each ensemble group shows a similar distribution of correlation skill (not shown). Although it is difficult to achieve reliable potential predictability from 5 ensemble simulations, the agreement between the 15 and 5 ensemble cases suggests that the CFS tends to have a larger inter-ensemble variance than the POAMA.

It should be noted that the strong response of monsoon circulation to SST variance is not always a positive factor in seasonal climate prediction, although it increases the potential predictability. As mentioned in Sect. 4.2, the prevailing role of SST, particularly over the ENSO region, on the WNP-EAM system in coupled models is one of the limiting factors in predicting the monsoon system.

Since the measure of potential predictability highly depends on the model being used, we further investigated relationships between potential predictability and practical forecast skill. Figure 10 shows a scatter plot between potential predictability (x axis) and practical TCC skill (y axis) for JJA 850 hPa zonal wind over the WNP-EASM region (110°E–155°E, 15°N–37.5°N). The results using December and April initial conditions are shown, which are the most nonlinear and linear cases, respectively. The results for the January case are similar to the December one and the results for the other months are closer to the April example. There are three important points in Fig. 10. First, comparing the potential predictability between different models does not lead to acceptable conclusions. There is no guarantee that a coupled model, which has a higher potential predictability, has a superior practical skill. In general, POAMA has a higher theoretical limit of correlation skill for JJA 850 hPa zonal wind over the region of interest than CFS but it has similar level of actual correlation skill with CFS. Second, in individual models, a linear relationship between potential predictability and actual skill tends to exist, especially in the case where the potential predictability is high. Finally, the relationship tends to depend on forecast lead time. It is noteworthy that the relationship shows a more nonlinear relationship when the JJA forecast is initiated from December or January. The JJA zonal wind forecast with other initial conditions shows a more linear relationship.

5 Improvement in the WNP-EASM precipitation prediction

5.1 Statistical postprocessing

It was shown in Sect. 3 that the long-lead prediction for the EASMI and WNPSMI is reasonably good in the current coupled models. In this section, we describe our attempts to improve the JJA precipitation prediction skill using better
predicted circulation field information. The statistical model for improving JJA precipitation is based on a multiple linear regression defined by

$$P(\text{lon}, \text{lat}, t) = a_1(\text{lon}, \text{lat})\text{EASMI}(t) + a_2(\text{lon}, \text{lat})\text{WNPSMI}(t)$$

where $P$ is the reconstructed JJA precipitation anomaly from two monsoon indices as a function of longitude, latitude, and year and $a_1$ and $a_2$ are the regression parameters for the anomaly of each index determined by a least-squares fit. If one index is used as the statistical model for predicting JJA precipitation, the regression coefficient for the other index equals zero. The regression parameters were calculated in a cross-validated manner, and, thus are different for each year. However, the difference is not large.

### 5.2 Results

We first applied the statistical model to the observed indices in order to obtain a potential prediction skill assuming that the EASMI and WNPSMI are perfectly predicted. Figure 11 shows the TCC skill for reconstructed JJA precipitation obtained from each separately observed index and from two indices together. Consistent with the design of each index, the EASMI anomaly is capable of reconstructing the JJA precipitation over many parts of the EASM region and the WNPSMI captures the interannual variability of JJA precipitation over most parts of the WNPSM region reasonably well. It should also be noted that the WNPSMI also represents variability over some parts of the IM and EAM regions. Figure 11c indicates that the combined EASMI and WNPSMI information potentially explain, to some extent, a large portion of the interannual variability of JJA precipitation over most of the oceanic region and some parts of the continental Asian monsoon region.

Figure 12 shows the TCC skill for JJA precipitation obtained from the statistical model with a MME prediction of two monsoon indices initiated from January to June, respectively. Because of the forecast errors for the predicted indices, the TCC skill underestimates the potential prediction skill from the observed indices (Fig. 11c), particularly over the EASM region. Nonetheless, the TCC skill for JJA precipitation obtained from the statistical model is much better than the skill for JJA precipitation from the simple MME prediction shown in Fig. 1. A large improvement is found over the EASM region particularly at a 5- and 4-month leads.

Figure 13 summarizes the impact of statistical postprocessing on improving precipitation prediction in terms of the anomaly PCC skill over the EASM and WNPSM regions. The results clearly show that forecast skill is significantly improved after applying statistical postprocessing at all forecast leads, especially over the EASM region. The conclusions also suggest the possibility for the long-lead prediction of JJA precipitation because the best skill is obtained in the case of a 4-month lead (February initial condition) for the EASM precipitation and a 5-month lead (January initial condition) for the WNPSM precipitation. It should be noted that the statistical postprocessing is more effective for predicting the EASM precipitation because the original MME prediction of JJA precipitation has a skill of almost zero, except for a 0-month lead forecast.

### 6 Summary and discussion

In this study, advantages and disadvantages of long-lead coupled predictions for the WNP-EASM precipitation and circulation were investigated using retrospective forecast data from NCEP CFS and BMRC POAMA for a 26-year period (1981–2006). Since predictions based on these two models are issued every month with an integration time of
Fig. 11 Temporal correlation skill for JJA precipitation obtained from linear regression model using contemporaneous JJA a EASMI, b WNPSMI, and c both indices in observation. The dotted contour represents statistical significance of the correlation coefficients at 0.05 confidence level.

Fig. 12 Same as Fig. 1 except after applying postprocessing using the JJA EASMI and WNPSMI obtained from MME.
9 months, it is possible to evaluate the forecast skill for JJA precipitation and circulation as a function of forecast lead time up to 6 months.

In order to assess the ability of the models to predict summer precipitation, TCC and PCC skills were used. The simple MME forecast skill over the WNPSM region increases with decreasing forecast lead time, whereas that over the EASM region is almost zero even at a 0-month lead (Fig. 1). When JJA 850-hPa zonal wind is taken into consideration, however, the performance of MME is good, indicating the possibility of long-lead predictions of the WNP-EASM system (Fig. 3). In fact, the MME has a significant prediction skill for the WNPSMI at a 4-month lead and for the EASMI at a 5-month lead.

It should be noted that the EASMI is mainly related to the preceding ENSO signal (Fig. 7) and simultaneous local SST variability (Fig. 6). On the other hand, for the case of WNPSMI, the more realistic lead–lag relationship between the index and ENSO contributes to a better skill for long-lead predictions, particularly in the case of CFS (Fig. 7b). Although ENSO is the major predictability source of seasonal climate systems, the conspicuous impact of the typical ENSO mode on the WNP-EASM circulation may limit the predictability of circulation in the current coupled models, since both models have difficulty in capturing other interannual variabilities in monsoon circulation which are not related to the typical ENSO variability.

In order to improve the long-lead prediction of the WNP-EASM precipitation, a statistical postprocessing method was developed using the EASMI and WNPSMI as predictors, which are more predictable than precipitation in both coupled models. The observed result first indicates that the combined information of the two indices have the potential to describe many aspects of the year-to-year variability of JJA precipitation over the Asian region (Fig. 11). The statistical postprocessing clearly resulted in an improvement of forecast skill for summer mean precipitation over most of the WNP-EASM region at all forecast leads (Fig. 12). In particularly, the MME prediction after applying statistical postprocessing has the best PCC skill for predicting EA precipitation at a 4-month lead and for WNP precipitation at a 5-month lead, indicating the potential for long-lead coupled climate predictions.

In relation to this potential for long-lead climate prediction, the seasonal variation of the upper-ocean mixed layer depth can be a crucial factor. The observed dynamical indices have significant lead–lag relationships with the variation in SST over the eastern Pacific, as shown in Fig. 7. The variability of SST can be attributed to seasonal variations in the depth of the surface mixed layer. Based on the ‘reemergence mechanism’ proposed by Alexander and Deser (1995) and Alexander et al. (1999) showed that SST anomalies that are initiated in February–March extend through a relatively deep mixed layer and persist at greater depths in the summer compared to those initiated in April–May over the eastern Pacific. In other words, SST anomaly formed in February–March can extend winter SST conditions into the summer season. The critical causes for a better skill for long-lead prediction will be investigated in future studies. In addition, further studies are needed to assess whether a January or February forecast is better than short-lead predictions for other coupled models.

The forecast skill over the continental monsoon region is still moderate even when statistical postprocessing is applied. The current study suggests two reasons for this. First, the current coupled models are not capable of capturing the interannual variability of the two monsoon indices unrelated to ENSO. In addition, the current coupled models have difficulty in simulating El Niño Modoki (or Central-Pacific El Niño) which is more related to the EASM variability than a typical El Niño (or Eastern-Pacific El Niño). Second, the ENSO mode of the coupled model has errors in spatial pattern and time evolution which result in errors in ENSO-monsoon teleconnections. Continuing improvement of the coupled model’s ENSO mode and improving the land-surface process and land initialization will further improve the long-lead prediction of the WNP-EASM systems.
In present study, we describe some attempts to improve the prediction of monsoon precipitation based on the performance of two coupled models. Adequate postprocessing such as the use of dynamical indices and the application of multiple linear regression can help raise the forecast skill for the long-lead seasonal prediction of other climate systems. However, the statistical postprocessing is only based on the dynamical characteristics. The amelioration of the physical process in coupled models will likely lead to improvements in the seasonal prediction skill for the WNP-EASM systems.

Acknowledgments This work was supported by a grant from the Korean Ministry of Environment as “Eco-technopia 21 project” and the second stage of the Brain Korea 21 Project. Lee and Wang acknowledge support from APEC Climate Center (APCC) international research project and IPRC, which is in part supported by JAMSTEC, NOAA and NASA. This is the SEOST publication number 7938 and IPRC publication number 697.

References


