

Seasonal prediction skill of APCC in-house models retrospective seasonal forecasts

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발간사

정확하고 신뢰도 높은 전 지구적 혹은 지역적 중장기 계절 예측 정보 제공을 위해서 전 지구 접합 모형은 필수적이며, 세계적 기관 및 대학에서도 지속적으로 모형 개발 및 개선을 통한 예측성 향상에 힘쓰고 있다. 본 센터는 매일 전 세계 우수기관으로부터 제공되는 계절 예측 정보를 활용하여 전 지구 다중 모형 앙상블 (MME) 예측 시스템을 운영하고 있다. 아울러 본 센터에서는 MME 예측성 향상에 기여하고자 APCC-CCSM3를 이용하여 매달 계절 예측 정보를 생산하고 있으며, 예측성 향상 및 응용분야의 활용연구 등을 위해 지난 수년간 고해상도 전지구 접합 모형인 Seamless Coupled Prediction System (SCoPS)를 개발한 바 있다.

본 연구보고서는 새롭게 개발된 SCoPS로부터 생산된 과거 예측 자료를 이용하여 계절 예측 성능을 다각도로 분석하고, 기존의 APCC-CCSM3의 결과와 비교·검증하여 SCoPS의 계통적 오차를 살펴보았다. SCoPS는 최근 그 필요성이 강조되고 있는 대기-해양 결합 초기화 방법을 사용하는 등 최신 기법을 포함하고 높은 해상도를 가지고 있어 기존의 CCSM3와 비교하여 볼 때 전반적으로 기온 및 강수를 비롯한 대기 대순환장 및 기후 변동성에서 개선된 모의 성능을 보인다. 특히 동아시아 기후의 핵심인 여름·겨울 몬순의 예측 성능은 다른 MME 참여 모형들인 세계적 기관들의 계절기후 모형들과 비교하였을 때에도 상위권으로 나타나 SCoPS의 우수성을 확인할 수 있다. 검증된 계절예측 정보는 역학적·통계적 상세화가 가능하여 수문, 농업 등 응용분야에서도 활용 가능하다는 점에서 더욱 의의를 갖는다.

본 연구보고서가 발간되기까지는 많은 분들의 도움이 있었다. 무엇보다도 연구가 순조롭게 진행될 수 있도록 다방면으로 도와준 임아영 연구원, 정혜인 연구원, 강수철 연구원, 그리고 본 연구보고서를 총괄하고 최종 집필한 본원의 함수련 박사에게 깊은 감사를 표하는 바이다. 본 연구보고서가 밑거름이 되어 향후 관련 연구들이 지속되고 부족한 부분들을 계속 채워나가길 바란다.

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ABSTRACT

This study describes the newly developed APCC in-house model, Seamless Coupled Prediction System (SCoPS). Using 32-year (1982–2013) ensemble hindcast runs produced with SCoPS and CCSM3, which is current operation system in APCC, this study evaluates the spatial and temporal structure of hindcast climatology, large-scale features, and prediction skills for major climate variability in both systems. A special focus is on the fidelity of the systems to reproduce and forecast phenomena that are closely related to the East Asian monsoon system. Overall, both CCSM3 and SCoPS exhibit realistic representations of the basic climate, although systematic biases are found for surface temperature and precipitation. Also, the SCoPS simulation provides a more realistic representation than CCSM3 for Walker and monsoon circulations based on analysis of upper tropospheric velocity potential, although it tends to overestimate the intensity of the Hadley circulation. Notably, SCoPS also captures the northward migrating rain band in May to August related to the Changma. In the case of East Asian monsoon index prediction, SCoPS show a higher correlation coefficient between observed and predicted indices than CCSM3 for both summer and winter seasons. The SCoPS simulation also demonstrates a useful skill in prediction of the wintertime Arctic Oscillation index based on EOF analysis. Based on results, it is clear that SCoPS is more skillful than CCSM3 in prediction of seasonal climate variability including ENSO, East Asian summer and winter monsoon, and the Arctic Oscillation. Consequently, this provides

criteria for understanding the characteristics of CCSM3 and SCoPS for providing seasonal climate forecasts. Also, it is clear that the SCoPS seasonal climate forecast will be useful for simulating the East Asian monsoon system within the MME prediction system.

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1. INTRODUCTION

Despite the chaotic internal dynamics of the atmosphere, time averaged atmospheric variables are predictable to some degree, due to those components that have slow variations on time scales from months to seasons (Kim et al. 2012). Global prediction systems have been continuously developed for operational medium-range weather forecasts and seasonal prediction (e.g., Molteni et al. 1996; Kusunoki et al. 2001; Saha et al. 2006, 2014; Arribas et al. 2011; MacLachlan et al. 2015). These are now being progressed into systems based on fully coupled climate system models that include comprehensive dynamics and physics of atmosphere, land surface, ocean, and sea ice interactions. Operational coupled seasonal forecast systems, including the Climate Forecast System from the National Center for Environmental Prediction (NCEP CFS) (Saha et al. 2014), European Centre for Medium-Range Weather Forecasts (ECMWF), UK Meteorological Office (UKMO) and Meteo-France (MacLachlan et al. 2015), as well as many research groups are continuously updating their seasonal prediction systems with improved physics and increased resolution.

For example, the horizontal resolution of the ECMWF Integrated Forecast System (Bechtold et al. 2008) model has been increased from TL159 in System 3 to TL255 in System 4. The UKMO has also increased the resolution of the seasonal prediction system into N216L85 for atmosphere, which is equivalent to 40 km horizontal resolution with 85 vertical levels (MacLachlan et al. 2015). There have been many studies that emphasize the importance of the physical parameterizations in seasonal prediction. Buizza et al. (1999) improved the medium-range forecast skill by stochastically perturbing tendencies calculated from the physical parameterization in the ECMWF system. Studies of Byun and Hong (2007) and Ham and Hong (2013) mentioned an important role of the cumulus parameterization in the seasonal prediction skill. In particular, Bechtold et al. (2008) and Park et al. (2010) showed that improved cumulus parameterization can give a higher prediction skill for tropical subseasonal variability. Also, an increasing number of studies have focused on initialization processes of the coupled prediction system. Koster et al. (2010) suggested that there is room for improved prediction skill for precipitation and surface temperature in land surface initialization. Kug et al. (2010) have developed

a new method using empirical singular vectors for perturbing initial conditions in ensemble seasonal prediction. Ham and Rienecker (2012) showed an improvement in ENSO prediction by improving the ensemble generation method in their 20-year hindcast simulation. Recently, Arctic sea ice concentration is also making it possible to initialize the sea ice model.

It has been demonstrated that fully coupled general circulation model is an ultimate tool for subseasonal to seasonal climate prediction. Since 2012, APCC has been provide the seasonal prediction data using the Community Climate System Model version 3 (CCSM3) with nudging of sea surface temperature (SST) from the Global Ocean Data Assimilation System (GODAS) (APCC CCSM3). The provision of seamless prediction in APCC will be a big challenge. However, as APCC has a significant contribution to many national hydrometeorological services within APEC. Also, as operational center for multi-model ensemble (MME) prediction, it is highly desirable to have an in-house climate prediction model. For this reason, APCC has completed the development of such a model, and generation of its retrospective data with a research group from the University of Hawaii, USA. The newly developed seamless climate prediction model is a fully coupled ocean, atmosphere, land, and sea ice component by OASIS coupler system.

Systematic validation of the prediction system based on historical reforecast (i.e., hindcast) data is one of the basic efforts needed to provide useful guidance for its further improvement. In this paper, the newly developed in-house global climate prediction model, termed the Seamless Coupled Prediction System (SCoPS), is described and evaluated alongside APCC CCSM3, with a primary focus on the fidelity of the system to reproduce and to forecast phenomena. The paper is divided into the following sections: Section 2 provides a brief description of the APCC CCSM3 and SCoPS framework for hindcast experiments; Section 3 examines hindcast climatology and prediction skills that are closely related to the East Asian climate; Section 4 summarizes the results and provides major conclusions.

2. MODEL AND PREDICTION SYSTEM

2.1 Overview of APCC CCSM3

APCC CCSM3 includes a SST data nudging method. CCSM3 has been designed to produce simulations with reasonable fidelity over a wide range of resolutions and with a variety of atmospheric dynamical frameworks. It is a community model system for climate simulation, which includes the Community Atmosphere Model version 3 (CAM3; Collins et al. 2004, 2006), the Community Land Surface Model version 3 (CLM3; Oleson et al. 2004; Dickinson et al. 2006), and the Community Sea Ice Model version 5 (CSIM5; Briegleb et al. 2004); the ocean component is based on the Parallel Ocean Program (POP) version 1.4.3 (Smith and Gent 2002). CAM3 is based on a Eulerian spectral dynamical core with triangular spectral truncation at 85 wavenumbers. Zonal resolution at the equator is 1.41° in the T85 configuration. The vertical dimension is treated using 26 levels with a hybrid terrain-following coordinate. The vertical grid transitions from a pure sigma region in the lowest layer, through a hybrid sigma-pressure region, to a pure pressure region above approximately 83mb. The land model is integrated on the same horizontal grid as the atmosphere, although each grid box is further divided into a hierarchy of land units, soil columns, and plant types. There are 10 subsurface soil layers in CLMs. Land units represent the largest spatial patterns of subgrid heterogeneity and include glaciers, lakes, wetlands, urban areas, and vegetated regions.

The ocean model is a Bryan-Cox-type, level-coordinated model with Boussinesq approximation. The model solves the primitive equations in general orthogonal coordinates in the horizontal direction subject to hydrostatic approximation. The barotropic equation is solved using a linearized, implicitly free-surface formulation. The model uses a dipole grid with a nominal horizontal resolution of 1° . The first pole of the semianalytic grids is located at the true South Pole and the second is located over Greenland (Smith et al. 1995). The vertical dimension is treated using a depth coordinate with 40 levels extending to 5.37 km. The spacing of grid points is 1.125° in the zonal direction and roughly 0.5° in the meridional direction with higher resolution near the equator. The sea ice model is integrated on the

same horizontal grid as the ocean model. The atmosphere, land, and sea ice components exchange fluxes and state information with the coupler every hour, while the ocean exchanges this data once per day. During integration, the coupler repeats a sequence of coupling operations including: transmission of data to ocean, land, and sea ice; reception of data from sea ice and land; transmission to the atmosphere; and finally, reception from the ocean and atmosphere.

Based on generally realistic initial conditions, SST-nudging which is an empirical method for data assimilation is used for initialization. In this method, the nudging term in the diagnostic equation includes observation information from extra/interpolation processes for ocean model resolution. The thermodynamic equation for the highest level in the ocean model is as follows:

$$\frac{\partial T}{\partial t} \dots = -\lambda(T - T_{obs}) \quad (1)$$

Here, T is the temperature at the highest level in the ocean model, simulated SST, T_{obs} is the observed daily SST, and λ is a Newtonian damping coefficient (5day⁻¹). In this study, the Newtonian damping coefficient is set as 1/5, based on the sensitivity test of Jeong et al. (2008). Further information on the APCC CCSM3 is given in Collins et al. (2006) and Jeong et al. (2008).

2.2 Overview of SCoPS

The International Pacific Research Center (IPRC) and University of Hawaii (UH) modeling group have recently developed a new coupled atmosphere-ocean model (POEM) which is based on the POP v2.0 model for the oceanic component, the Ocean-Atmosphere-Sea Ice-Soil (OASIS v3.0) coupler, and ECMWF-Hamburg Atmospheric Model (ECHAM v4.6) as the atmospheric component (Xiang et al. 2012). They have demonstrated that the coupled model has a realistic mean state and variability of SST, precipitation, and atmospheric circulation. In particular, many efforts have been made to improve the ENSO simulation in POEM. As APCC is a leading center for MME prediction, it is highly desirable to have an in-house model for climate prediction. For this reason, APCC has developed its own fully coupled climate model for seamless prediction of weather and climate, SCoPS, based on an

improved version of the POEM model with integrated atmosphere-ocean initialization processes.

Compared with the POEM model (Xiang et al. 2012), the following changes have been made for SCoPS:

- 1) Updating the coupler from OASIS3.0 to OASIS3-MCT, which is interfaced with the Model Coupling Toolkit (MCT) (Larson et al. 2005). MCT implements fully parallel regridding and parallel distributed exchanges of variables, making the exchange of variables during coupling more efficient than in OASIS3.0
- 2) Implanting the sea ice model (CICE4.1)
- 3) Increasing the ocean model resolution from 3° to 1°
- 4) Updating ECHAM v4.6 to ECHAM v5.3 and increasing the resolution from T42L19 to T159L31
- 5) Improving the land surface model

ECHAM5 is the fifth generation of the ECHAM atmospheric model. The model employs a spectral dynamic core and utilizes a semi-implicit leapfrog time differencing scheme. Vorticity, divergence, temperature and the logarithm of surface pressure are represented in the horizontal direction by a truncation of spherical harmonics. Triangular truncation is used at wavenumber 159. A hybrid coordinate system is used in the vertical direction with top to 10hPa: a sigma system at the lowest model level gradually transforms into a pressure system in the lower stratosphere. A flux from a semi-Lagrangian scheme (Lin and Rood 1996) is used for passive tracer transport, that is, for all water components and chemical substances. Land surface temperature is obtained from the surface energy balance equation using an implicit coupling scheme that is unconditionally stable and allows us to synchronously calculate the respective prognostic variables and surface fluxes. Surface temperature is used as a boundary condition to determine the vertical profile within the five-layer soil model assuming vanishing heat fluxes at the bottom (10m depth). For a more detailed description of ECHAM5 and the land surface model refer to Roeckner et al. (2003) and Hagemann et al. (2006).

General information in the ocean model is same as for POP in APCC CCSM3,

but with improved physics. The model configuration is derived from CCSM3, with 320 horizontal (zonal) x 384 (meridional) grid points (meridionally about 0.3° in the near equatorial region) and 40 vertical levels. The vertical resolution is about 10m in the upper 100m. A solar absorption component based on specified monthly mean surface chlorophyll concentrations (Ohlmann 2003) is also imbedded. The CICE v4.1 model has several interacting components: 1) a thermodynamic model computing local snow and ice growth rates due to vertical conductive, radiative, and turbulent fluxes, as well as snowfall; 2) a dynamic model that predicts the velocity of the ice pack; 3) a transport model that describes advection of the areal concentration, ice volumes, and other state variables; and 4) a ridging parameterization that transfers ice between thickness categories based on energetic balances and rates of strain. More details can be found in Hunk and Lipscomb (2010).

OASIS3-MCT is interfaced with the MCT (Larson et al. 2005) developed by the Argonne National Laboratory in the USA. MCT implements fully parallel regridding and parallel distributed exchanges of the coupling fields, based on pre-computed regridding weights and addresses. All component processes and all couplings are now executed in parallel, directly between the components via MPI. There are 36 variables in total to exchange between these three model components through the coupled OASIS3-MCT. Interpolation of heat flux conservation is adopted to keep energy conservation, thereby avoiding climate drift in the coupled system. Atmosphere, ocean, and ice models exchange information once a day. A schematic diagram of the coupling and exchange field for each model component is shown as Fig. 1.

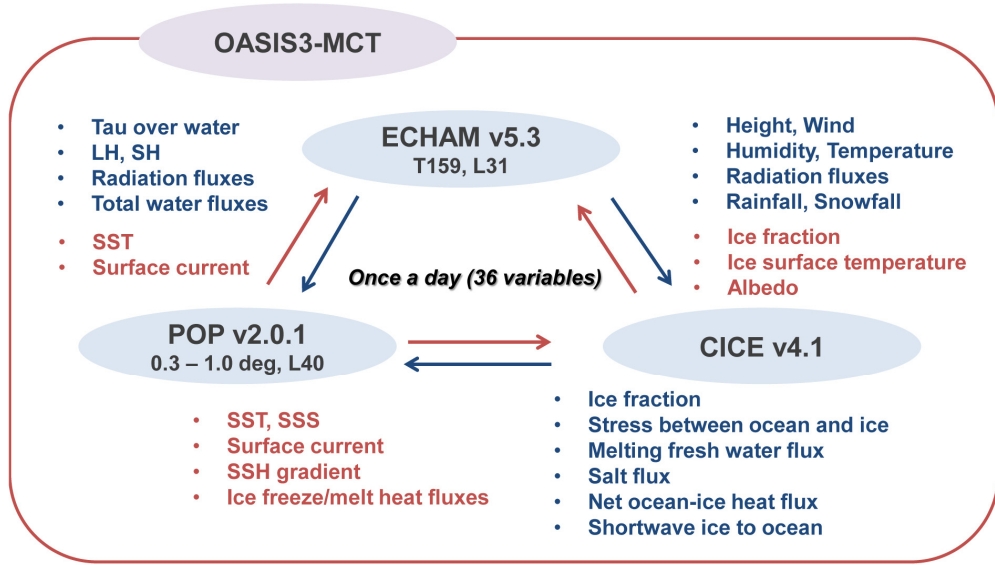


Figure 1 Schematic diagram of coupling and exchange field for each model component.

High quality climate forecasting relies on, and requires improvement of climate models, use of advanced data assimilation methods that make full use of observation data. A synthesized atmosphere-ocean (AO) initialization scheme has been developed, which combines 3-D atmospheric initialization and Ensemble Adjustment Kalman Filter (EAKF) ocean initialization. This approach takes advantage of current available analysis or reanalysis datasets to generate model-compatible atmospheric initial conditions through 3-D nudging. To generate perturbed initial conditions for the ensemble hindcasts and forecasts, three major steps are taken: 1) generation of model-compatible data set from analysis data sets; 2) nudging the model-compatible 3-D data into the model; 3) generation of perturbed ensemble initial conditions. It uses a simple method, in which seasonal-dependent perturbation fields of u , v , t , and q are generated with long-term free integrations first, then they are scaled and added into analysis fields to generate the ensemble initial conditions.

The EAKF for ocean assimilation is implemented following the pioneering work of Zhang et al. (2007). The detailed mathematical derivation of EAKF can be found in Anderson (2001). The EAKF data assimilation process mainly includes two steps: observational increment and projection. The first step is to calculate the observational increment at the observation location. We calculate the updated y_k^u first by using

the following equation:

$$y_u^k = \frac{y_u^p}{1 + r_k^2} + \frac{y_k^o}{1 + r_k^{-2}} \quad (2)$$

Here, p is the prior estimate, o is observation, u is updated, and k is the observational index. We will also use x_i in the following, where i represents the index for a model grid point. In equation (2), y_x^p is calculated from x_i^p using tri-linear interpolation; $r_k = \frac{\sigma_{k,k}^p}{\sigma_{k,k}^o}$, $\sigma_{k,k}^o$, and $\sigma_{k,k}^p$ represent observational error and its prior estimate from the ensemble. Then the observational increment is:

$$\Delta y_k = y_k^u - y_k^p \quad (3)$$

After obtaining the observational increment, the second step is to make use of the covariance between observational locations and model grid points to project the observational increment to the model grid point increment.

$$\Delta x_i = \frac{C_{i,k}^p}{\sigma_{i,i}^p} \Delta y_k \quad (4)$$

Here, $C_{i,k}^p$ represents the covariance between the model grid point and observation location. Following these processes, all observations are assimilated sequentially. To optimize use of computer processors for EAKF calculations, a parallel scheme is employed.

2.3 Hindcast simulation

APCC CCSM3 and SCoPS are fully coupled general circulation models that provide operational seasonal predictions. Both systems provide reforecast simulations for evaluating and calibrating the model simulation. APCC CCSM3 seasonal reforecasts, commencing in 1982, include 10 member ensembles in a time lagged forecasting method consisting of 7-month simulations initialized on the 1, 6, 11, 16, 21, and the last 5 days of every month for atmosphere and ice, and from the 22–26 of every month. For Initial data, the CAM3 atmosphere model is integrated for the

period from 1971 to 1981 (11 yr) using GODAS SST (Behringer et al. 1998) and 600-year spin-up data from NCEP reanalysis data 2 (Kanamitsu et al. 2002). Using flux data from the atmospheric run, the POP ocean model is executed for the same period. This data is initialized and nudged for realistic initial conditions using GODAS SST every day from Jan. 1, 1982 by linear interpolation and extrapolation.

In this study, long-term hindcast experiments using SCoPS were conducted for a 32-year period (1982–2013). Hindcast runs commenced at fixed calendar dates — the 1st and 5th of each month — with 5 ensemble members perturbed by ENKF and integrated up to 7 months. The ensemble initial conditions are from the first EnOI results (Jan. 1, 2001–2012). The stationary ensemble vector is calculated using the results from a 100-year free run simulation. In this system, observed temperature (T) and salinity (S) are not only used to correct themselves but also used to correct each other since the conservation of T-S balance has been shown to be an important factor for successful data assimilation (Zhang et al. 2007). Vertically, only profile data above 400m is used since the deeper ocean is not expected to affect the seasonal forecast skill. Spatially, observational data from the band between 50°S–50°N is used. Initialized data (Jan. 1, 2013) is assimilated every day from Jan. 1, 1982 using NCEP CFS reanalysis data and subsurface profile data including mechanical bathythermograph data (MBT), expendable bathythermograph data (XBT), profiling float data (PFL), ocean station data (OSD), conductivity-temperature-depth data (CTD), drifting buoy data (DRB), and Moored buoy data (MRB). Also, for operational forecast, the real time ocean data used Argo profiles, which are available online: <ftp.usgoda.gov/pub/outgoing/argo/>

For forecast evaluation, SST data is obtained from monthly NOAA Optimum Interpolation (OI) SST V2 (Reynolds et al. 2002). Air temperature at 2m (T2m), mean sea level pressure (SLP), wind vector, and geopotential height data are obtained from the NCEP reanalysis 2 (RA2) and ERA-Interim reanalysis products (Kanamitsu et al. 2002; Dee et al. 2011) from 1982. The Global Precipitation Climatology Project (GPCP) version 2.1 combined precipitation dataset (Adler et al. 2003) and Asian Precipitation — Highly-Resolved Observational Data Integration Towards Evaluation of the Water Resources (APHRODITE) data sets (Yatagai et al. 2012) are used as validation.

3. RESEARCH RESULTS

3.1 Systematic bias

Accuracy of SST prediction is one of the most important factors that define the quality of the seasonal prediction system, as a large portion of the interannual variability is explained by tropical SST. Figure 2 compare the seasonal-mean SST for JJA and DJF from OISST observations with those constructed using 3-month lead data from CCSM3 and SCoPS hindcasts. Both CCSM3 and SCoPS represent the observed SST patterns reasonably well in both seasons, such as the Indo-Pacific warm pool region and the cold pool region in the equatorial eastern Pacific. The sharp gradient in SST from the subtropics to high latitudes is also reasonably resolved in both models. As shown in Fig. 3, a systematic error in the SST prediction is also noticeable, particularly in the equatorial eastern Pacific where the observed cold SST region is overestimated in both models. This bias is often referred to as the “cold tongue” problem and is common in many ocean-atmosphere coupled climate models (e.g., Davey et al. 2002; Misra et al. 2008). This cold tongue problem is reduced in SCoPS compared with CCSM3. Also, there is a remarkably systematic cold bias over the northwestern Pacific in SCoPS.

Figure 4 shows the 2-m temperature distribution for JJA and DJF obtained from ERA-Interim reanalysis data, CCSM3, and SCoPS. For both JJA and DJF, the hindcasts generally well capture the observed distribution. The sharp gradient in surface temperature is also reasonably represented in both models. As shown in Fig. 5, systematic bias in surface temperature prediction is significant, especially cold biases over North America and warm biases over the Eurasia region in the SCoPS hindcast. There are slight warm biases over the Eurasia region in CCSM3 hindcast. The large biases in the SCoPS hindcast are maybe due to the fact that, although there is no initialization for land variables, it does not well represent land processes as it has fewer soil layers in the land surface model (CCSM3 has a 10-layer soil and SCoPS has a 5-layer soil). However, detailed validation including radiation and moisture flux exchanges is needed to clarify understanding of the biases.

Figure 6 compares the horizontal distribution of precipitation in JJA and DJF. In GPCP observations, the mean precipitation pattern is characterized by peaks over the western Pacific, South China Sea, Bay of Bengal, south eastern equatorial Indian Ocean, as well as zonally-elongated rain bands (intertropical convergence zone, ITCZ) over the Pacific and Atlantic oceans. The CCSM3 and SCoPS hindcast climatology captures the observed wet regions reasonably well, although different wet and dry biases are notable in the two models. In JJA (Figs. 7a, b), the CCSM3 simulation tends to overestimate rainfall over the equatorial central Pacific and parts of the Indian Ocean. Dry biases are also found in the Atlantic ITCZ, western Pacific, parts of the Indian Ocean, and the northeastern Pacific. Conversely, the SCoPS simulation generally tends to overestimate precipitation over the central Pacific ITCZ, the Atlantic ITCZ, and maritime continental regions. Some dry biases are also found in the southern central Pacific ITCZ. In DJF (Figs. 7c, d), the CCSM3 hindcast shows wet biases over the eastern Pacific and western Indian Ocean, and dry biases over the eastern Indian Ocean. Conversely, the SCoPS simulation tends to overestimate rainfall over the central Pacific ITCZ as well as the western and eastern Pacific in the Northern Hemisphere winter. These biases tend to drive a double-ITCZ pattern in the central Pacific (Zhang and Wang, 2006; Hwang and Frierson 2013). Also, for both models it is noted that the wet biases straddling north and south of the equator, and dry bias at the equator, seem not to be totally independent of the cold tongue bias in SST (See Fig. 3).

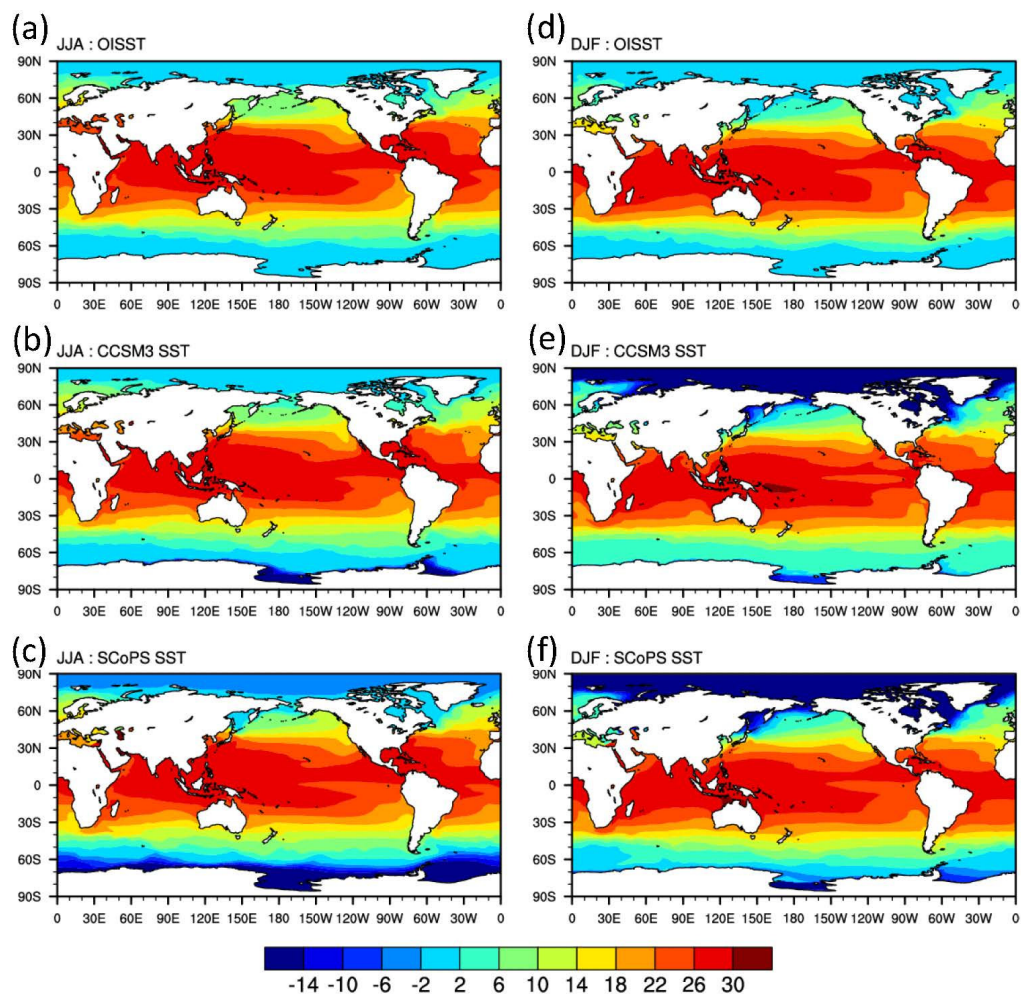


Figure 2 Seasonal-mean SST in JJA (left) and DJF (right) from OISST observation (top), and hindcasts with 3-month lead time from the CCSM3 (middle) and SCoPS (bottom).

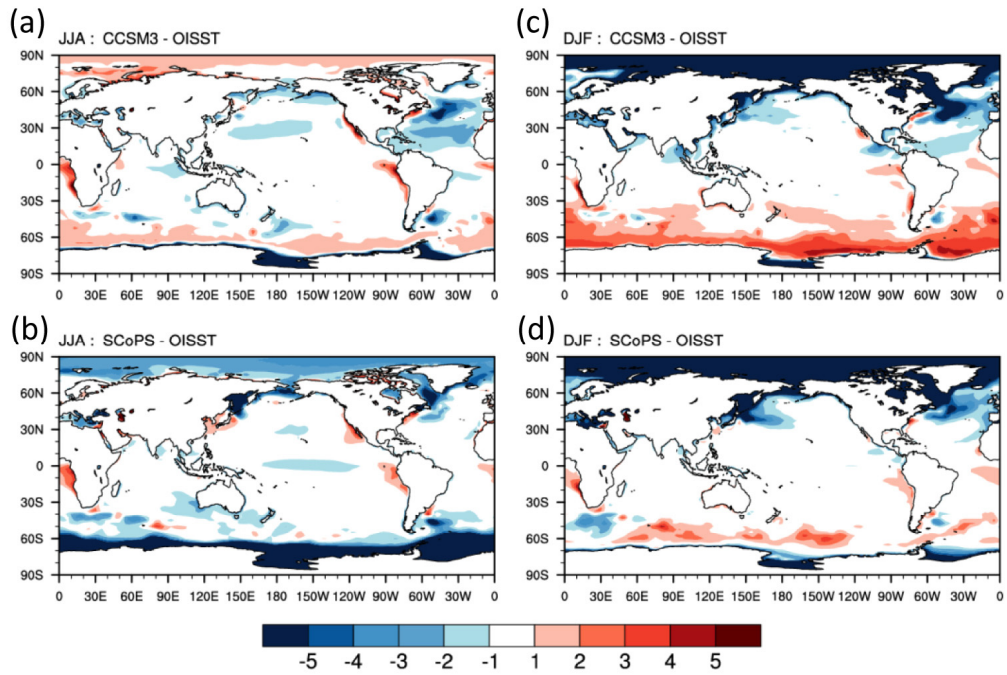


Figure 3 Climatological summer (left) and winter (right) bias (model minus observation) in SST for: (a), (c) CCSM3; and (b), (d) SCoPS.

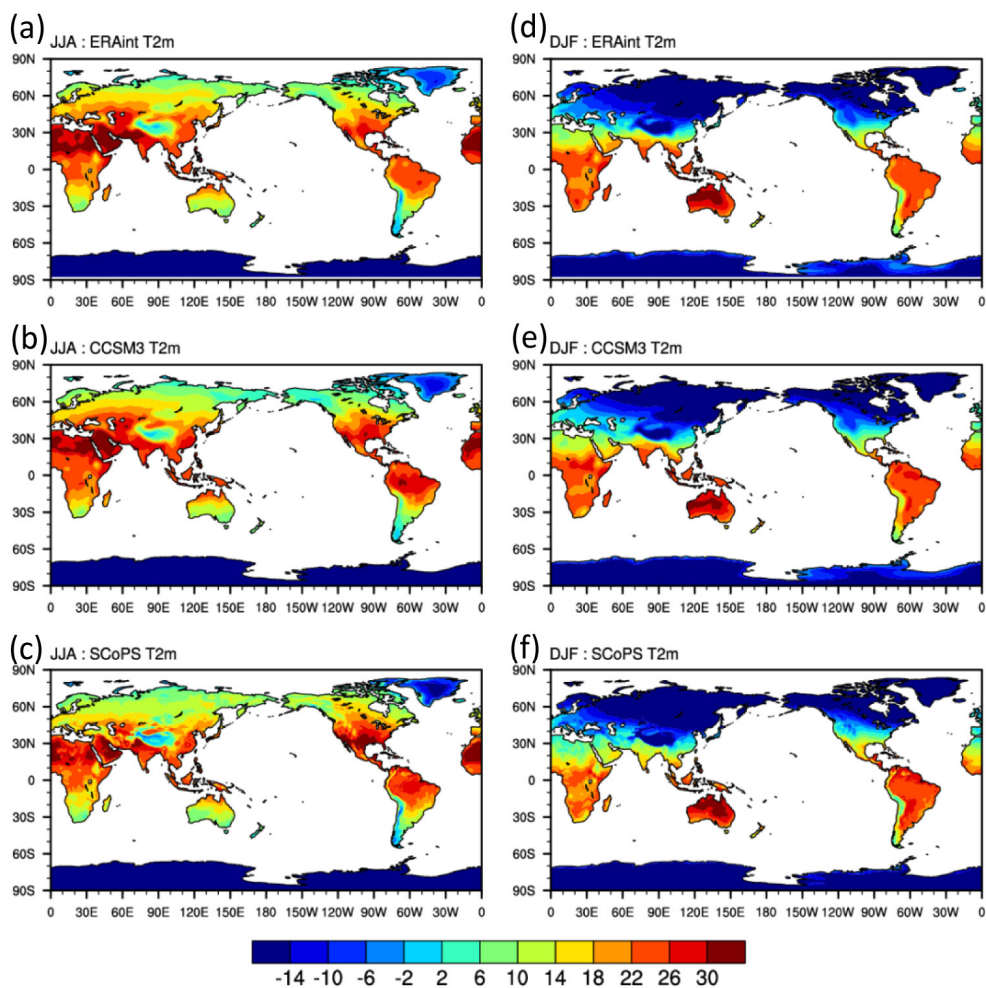


Figure 4 Seasonal-mean 2m temperature in JJA (left) and DJF (right) from ECMWF interim reanalysis data (top), and hindcasts with 3-month lead time from the CCSM3 (middle) and SCoPS (bottom).

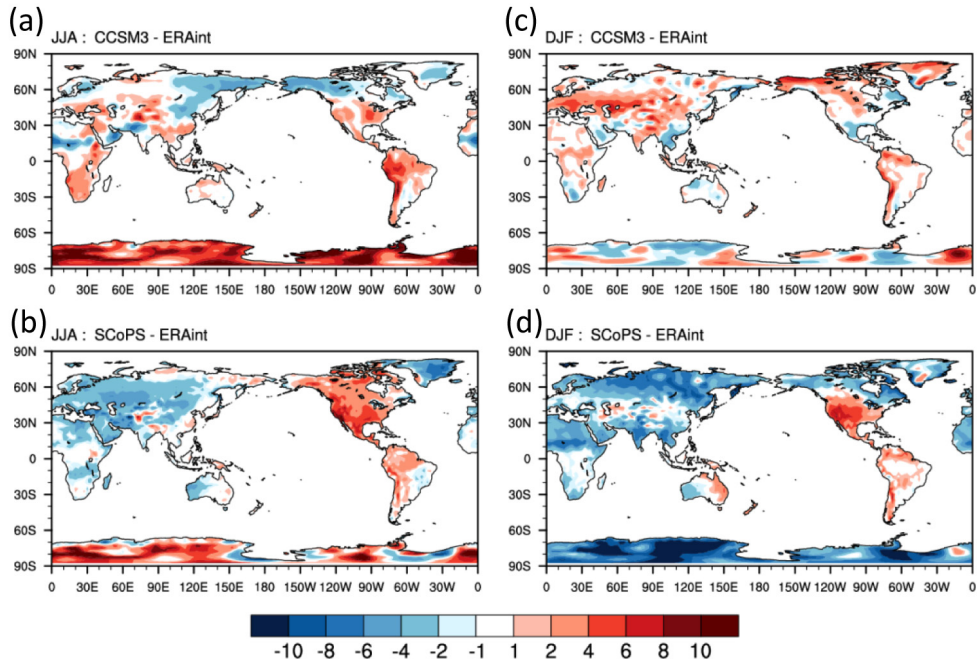


Figure 5 Climatological summer (left) and winter (right) bias (model minus observation) in 2m temperature for: (a), (c) CCSM3; and (b), (d) SCoPS.

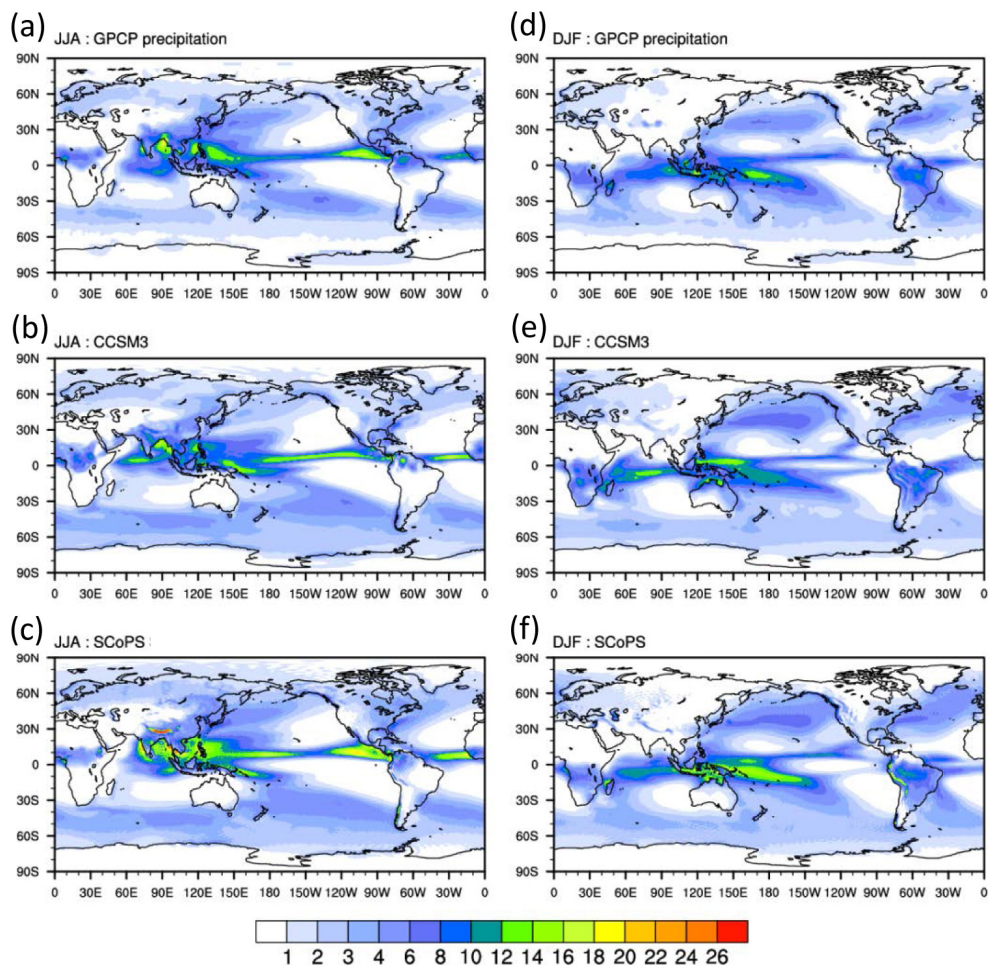


Figure 6 Seasonal-mean precipitation in JJA (left) and DJF (right) from GPCP observation (top), and hindcasts with 3-month lead time from the CCSM3 (middle) and SCoPS (bottom).

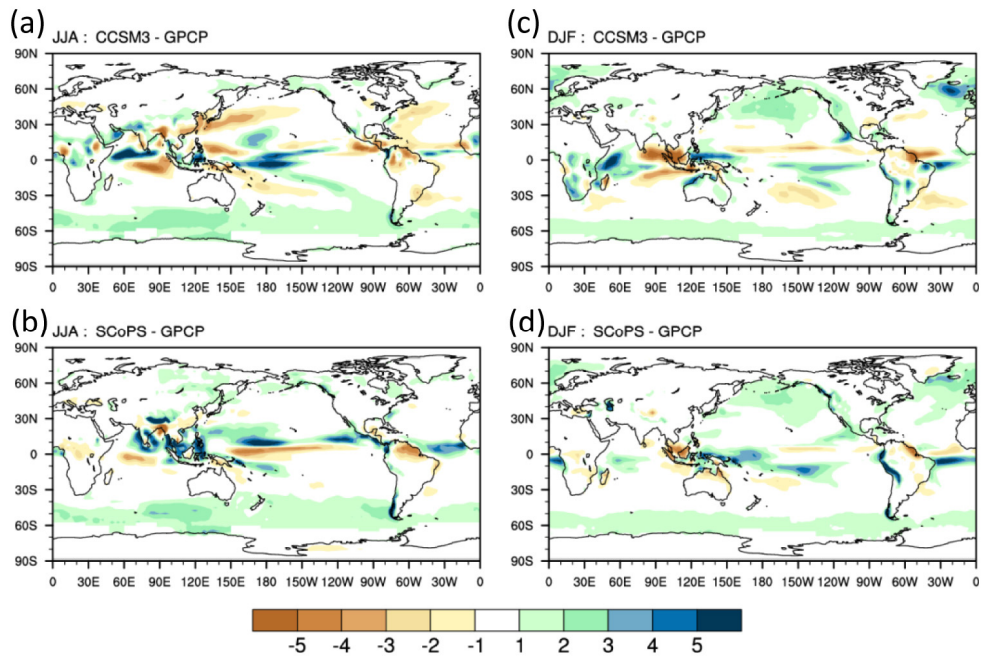


Figure 7 Climatological summer (left) and winter (right) bias (model minus observation) in precipitation for: (a), (c) CCSM3; and (b), (d) SCoPS.

3.2 Large-scale tropical circulation

Large-scale tropical circulation, such as Hadley, Walker, and monsoon circulations are the strongest driving force of the general circulation in low latitudes and their year-to-year variations greatly impact Earth's climate variability. The circulations are tightly coupled with each other, producing the strongest convection center around the western equatorial Pacific (Tanaka et al. 2004). This study attempts to divide the global divergent field in the upper troposphere into contributions from the Hadley, Walker, and monsoon circulations using the seasonal-mean (JJA, DJF) velocity potential field at the 200hPa-level following Tanaka et al. (2004). Tanaka et al. (2004) mentioned that the velocity potential at the 200hPa-level contains information concerning the overall intensity of the Hadley, Walker, and monsoon tropical circulations. These tropical circulations are driven by different dynamical causes. For example, the Hadley circulation in the general circulation context is driven by meridional differential heating, while the Walker circulation is driven by differences in SST along the equatorial tropics. Thus, the main driver of the Walker circulation may be the asymmetric zonal distribution of SST created by the major oceanic circulations. The land-sea distribution can drive the monsoon circulation due to heat contrast. Therefore, the annual cycle with seasonal reversal in the direction of the circulation between summer and winter may be the essential component in definition of the monsoon.

Based on this argument, Tanaka et al. (2004) first defined the Hadley circulation as an axisymmetric part of the circulation. This assumes that information is contained in the zonal mean field of the velocity potential. Also, they assumed that information on the Walker and monsoon circulations is contained in the deviation field from the zonal mean. Second, they defined the monsoon circulation as part of the seasonal change of the deviation field. For this reason, the seasonal-mean is subtracted from the deviation field to define the monsoon circulation. Finally, they defined the Walker circulation as the remainder, which is the annual mean of the zonal deviation field. More detailed definition and analysis from field observation can be found in Tanaka et al. (2004). In this study, two hindcast simulations representing information on large-scale circulation from velocity potential are evaluated through comparison with the same information from other reanalysis data.

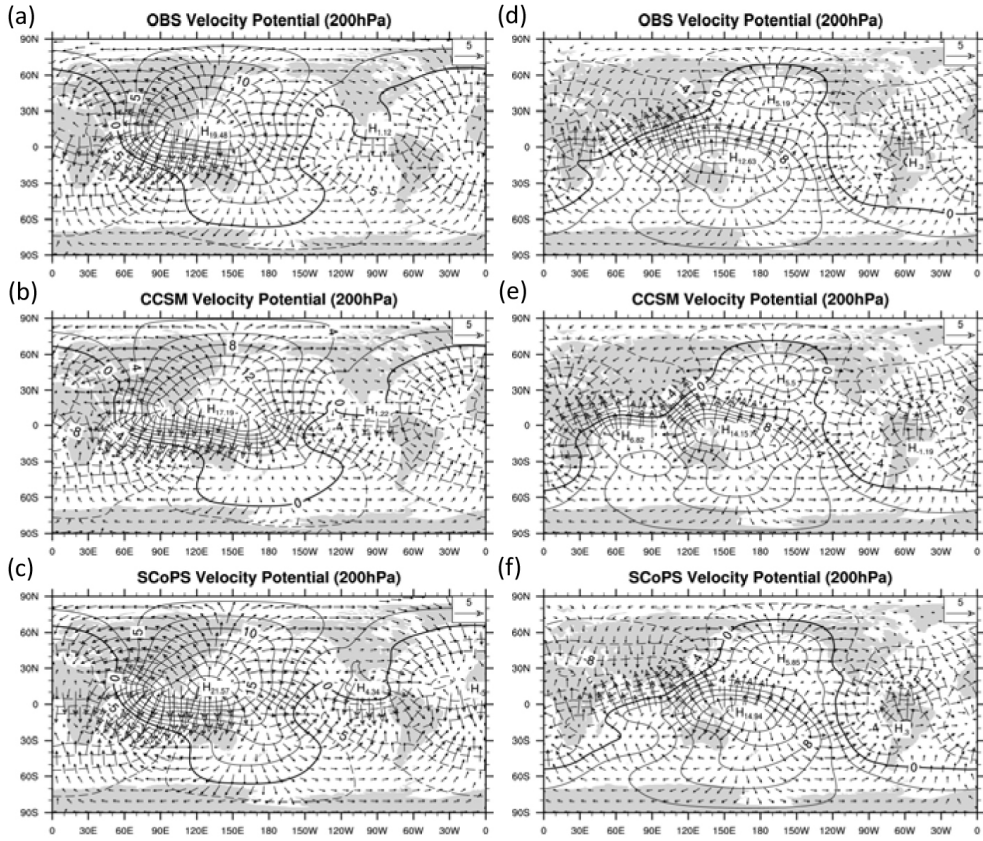


Figure 8 Monthly mean velocity potential and divergent wind at 200hPa for the hindcast period (1982–2013) with 3-month lead time for JJA (left) and DJF (right). The units are $10^6 \text{ m}^2 \text{ s}^{-1}$.

First, the seasonal variation in velocity potential of the climatological mean is compared before examining the interannual variability of the tropical circulations. Figure 8 shows the seasonal-mean velocity potential and divergent wind at 200hPa averaged for JJA and DJF. In observed distributions (Figs. 8a, d), a positive peak in the velocity potential with a value of nearly 20 ($\times 10^6 \text{ m}^2 \text{ s}^{-1}$) is located northwest of the Philippines in JJA. The minimum is seen over the southern Atlantic Ocean, with a value of -10 ($\times 10^6 \text{ m}^2 \text{ s}^{-1}$). Hereafter, the velocity potential “units” of measurement are assumed to be $10^6 \text{ m}^2 \text{ s}^{-1}$ for simplicity. Strong divergent wind from the Northern Hemisphere to the Southern Hemisphere is associated with the Hadley circulation. In DJF, the positive peak reaches its full weakness with a value of 12 units and its location has shifted to the equatorial western Pacific. The location

of the minimum is also shifted to western Africa. The convection center located near the Philippines in JJA results from the combination of the Asian monsoon, Walker, and Hadley circulations. In DJF, the center moves to the north of Australia, associated with the Australian monsoon. The seasonal variation caused by the land-sea thermal contrast may be a component of the monsoon circulation. The zonal mean component of the meridional circulation, which reverses direction over the equator between winter and summer, may be regarded as the Hadley circulation contribution.

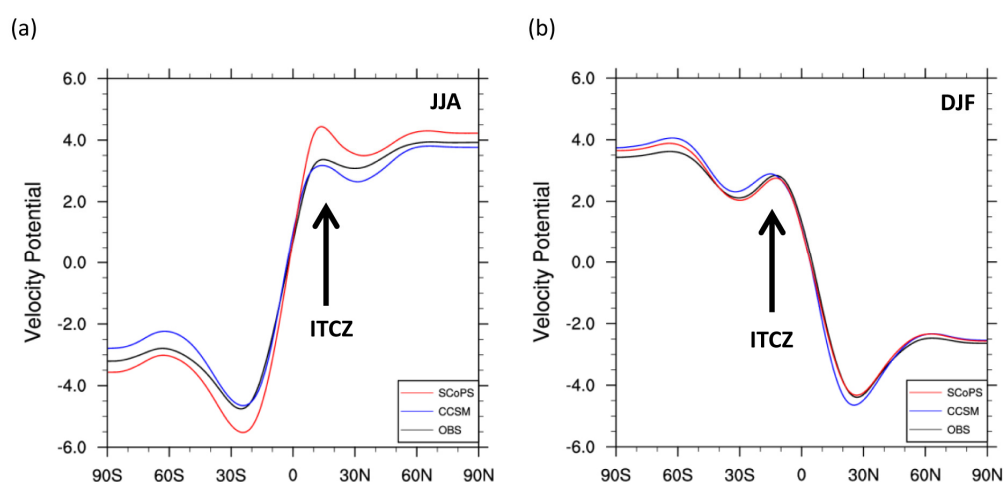


Figure 9 Zonal mean of the velocity potential in Fig. 8 for summer (left) and winter (right) for reanalysis data (black line), CCSM (blue line), and SCoPS (red line) hindcast with 3-month lead time. The units are $10^6 \text{ m}^2 \text{ s}^{-1}$. Hadley circulation is defined by the zonal mean.

The zonal mean of the velocity potential in climate is presented in Fig. 9 for JJA and DJF. In the observed data, the velocity potential at 200hPa is positive in the Northern Hemisphere, and peaks at 15°N , and negative in the Southern Hemisphere, with the corresponding peak at 20°S in JJA. These peaks represent the locations of sinking and rising motions in the zonally symmetric meridional divergent flow from the Northern to Southern Hemisphere. A strong zonally symmetric divergent wind flows from the Northern to Southern Hemisphere, indicating a pronounced over turning of the Hadley circulation cell over the equator. The ITCZ associated with the Hadley circulation is located at 15°N where the positive peak is seen in Fig. 9. In DJF, the velocity potential at 200hPa is negative in the

Northern Hemisphere with its peak at 25°N . The meridional divergent wind is obviously weaker than that in JJA. The pronounced meridional divergent flow over the equator clearly represents the upper tropospheric branch of the zonally symmetric Hadley circulation in the boreal winter. The peak in velocity potential does not necessarily coincide with the core of the upward motion, yet they are known to coincide for plain waves.

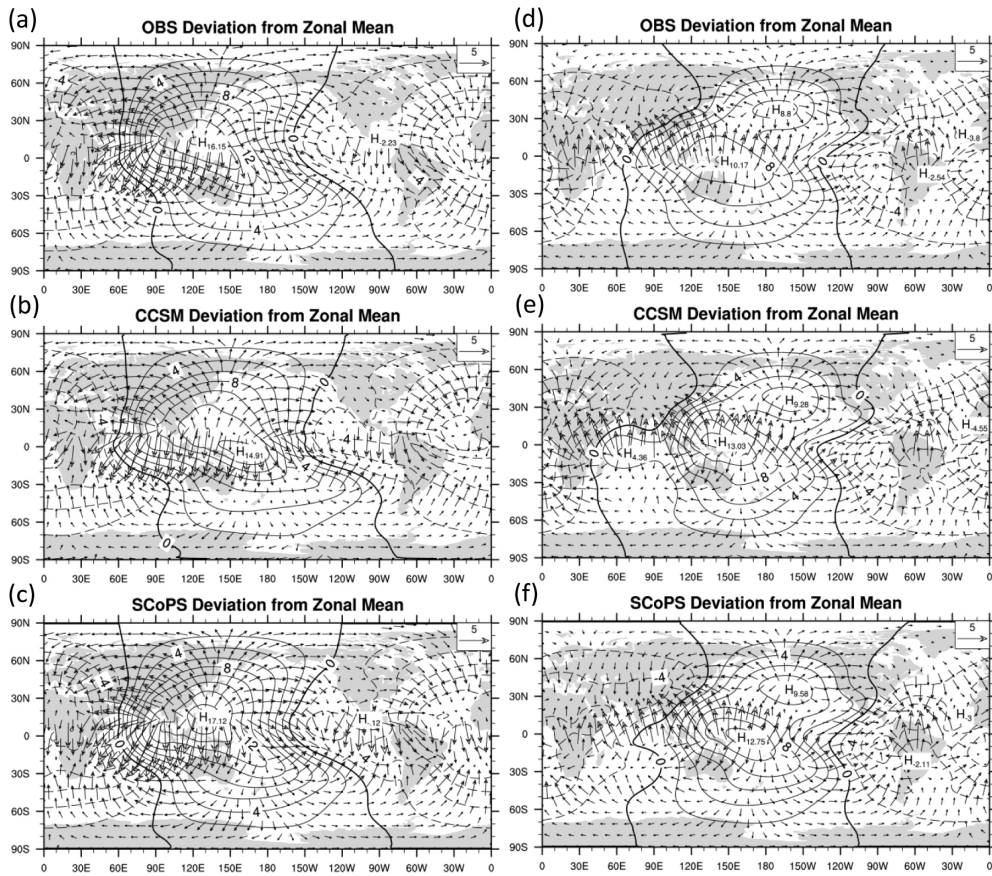


Figure 10 Deviation from the zonal mean of velocity potential for summer (left) and winter (right) for mean climatology from reanalysis data (top), CCSM3 (middle), and SCoPS (bottom) with 3-month lead time. The units are $10^6 \text{ m}^2 \text{ s}^{-1}$.

Both hindcast simulations well represent the zonal mean velocity potential at 200hPa, which represents seasonal change of the Hadley circulation, and in JJA,

the positive and negative peaks are also well captured. However, the SCoPS simulation tends to overestimate its intensity, while the CCSM3 run shows weak intensity over peak regions in summer. In DJF, the SCoPS simulation plots closer to the observation than the CCSM3 simulation because the divergent wind from CCSM3 is stronger than that from SCoPS.

Figure 10 illustrates the deviation field of velocity potential from the zonal mean for observations, CCSM3, and SCoPS in JJA and DJF, calculated by subtracting the zonal mean in Fig. 9 from the raw value in Fig. 8. Because the Hadley circulation has been removed, by definition the pattern should contain the Walker and monsoon circulations. A dominant pattern in both seasons indicates the Walker circulation, with rising motion over the western Pacific and sinking motion over the eastern Pacific as well as over the Atlantic. Both simulations also generally well represent these rising and sinking motions. In JJA, observations show the positive center is in approximately the same location compared with that in Fig. 8, but its intensity is 160 units. The positive center is almost symmetric about the equator, and it is broadened meridionally. In DJF, observations show the location of the positive peak moves slightly to the western Pacific, and the peak value decreases to 10 units. Another weak positive center is seen over the north Pacific. The negative peak is split into two centers over the equator, the eastern Pacific and eastern Atlantic. Both simulations generally represent the observed features well. However, the CCSM3 simulation for JJA shows the peak location is shifted eastward. The SCoPS simulation tends to overestimate the peak value in summer, but the CCSM3 shows an intensified value in winter. Also, it is clear that the CCSM3 run shows an additional positive peak over the Indian Ocean, which is never seen in observations. However, both simulations represent the dominant zonal wavenumber well, one associated with the Walker circulation, and the monsoon circulation which is hidden as a minor component of seasonal change compared with the observed features.

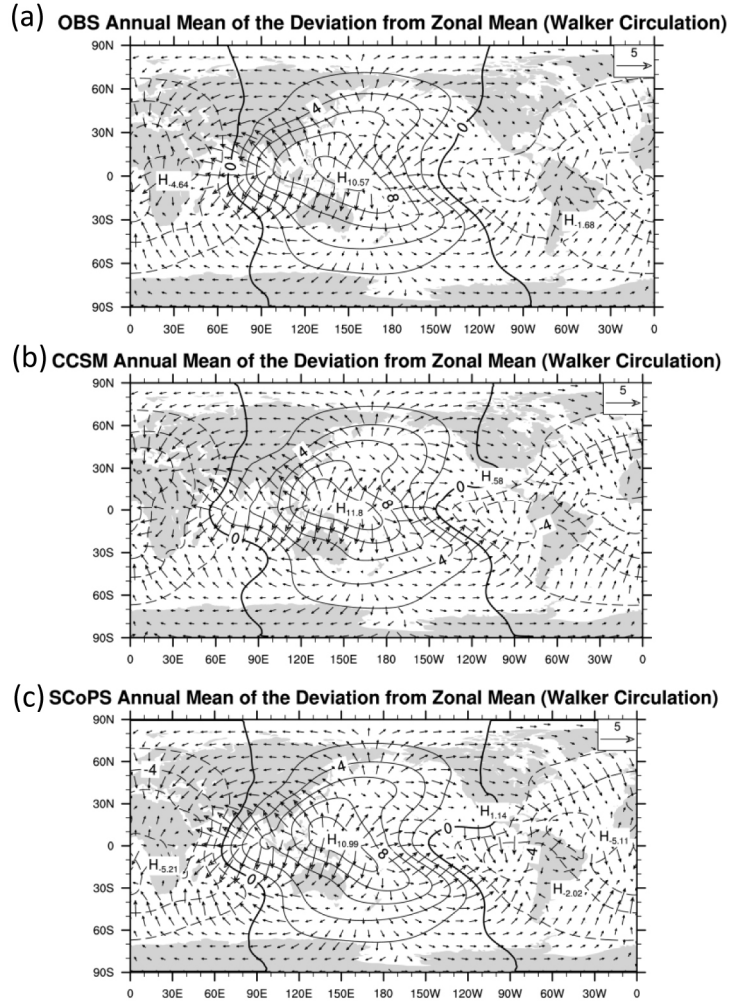


Figure 11 Annual mean (hindcast with 3-month lead time starting from Feb., May, Aug., Nov..) of the velocity potential in Fig. 10. The units are $10^6 \text{ m}^2 \text{ s}^{-1}$. The divergent wind is also plotted from the velocity potential field. The Walker circulation is defined using the annual mean of the velocity potential in Fig. 10.

By the definition, the annual mean does not have to see the monsoon circulation because seasonal change. The monsoon circulation should be included in seasonal change, and the component represented in the annual mean component should be the Walker circulation. For this reason, the zonal deviation field in Fig. 10 can be divided into annual mean and the seasonal change components. Figure 11 shows the annual mean of the zonal deviation field in Fig. 10. The divergent wind is also

plotted on the velocity potential field. In the observed data, the pattern clearly describes information on the Walker circulation, with the center of upward motion in the equatorial western Pacific and downward motion in the eastern Pacific. Downward motion is also seen at the equatorial eastern Atlantic. Thus, the annual mean component in Fig. 11 is clearly a reasonable representation for the Walker circulation. Both simulations represent the upward motion in the equatorial western Pacific and downward motion in the eastern Pacific very well. However, CCSM3 shows a stronger intensity in the upward motion; the intensity of the Walker circulation is more than 10 units, which is about three times stronger than that of the Hadley circulation. Although SCoPS tends to overestimate the intensity of Hadley circulation, the intensity of the Walker circulation is reasonable.

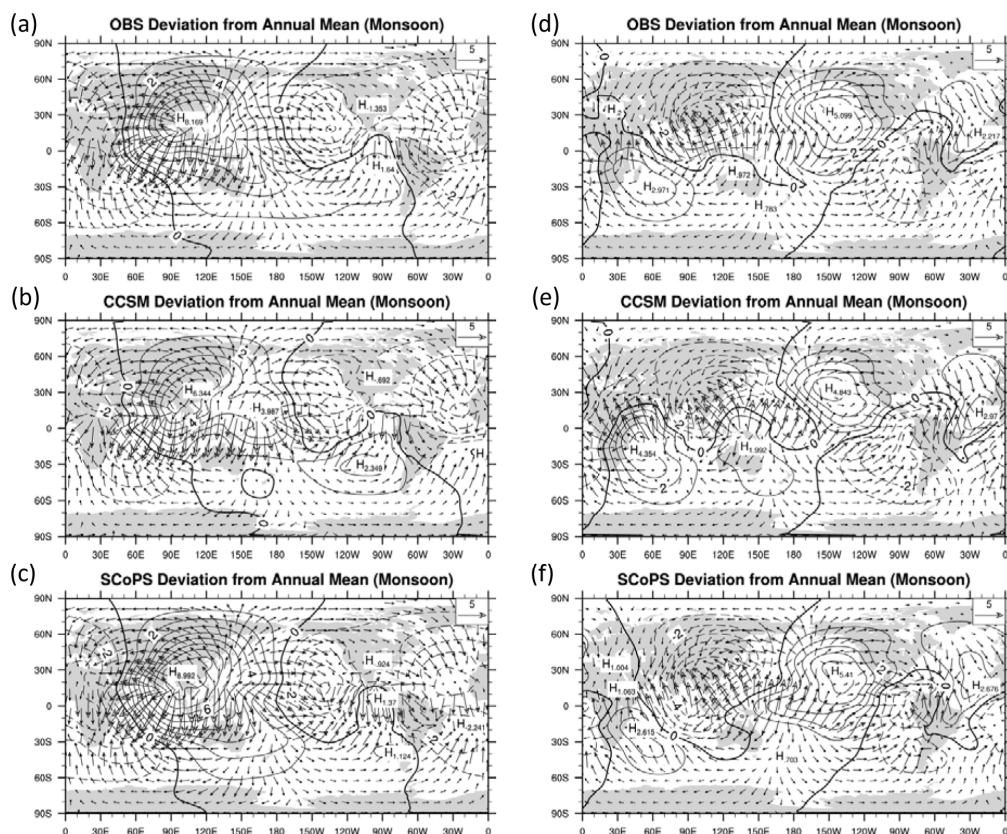


Figure 12 Deviation from the annual mean of the velocity potential in Fig. 10 for summer (left) and winter (right) climatologies. The divergent wind is also plotted from the velocity potential field. The units are $10^6 \text{ m}^2 \text{ s}^{-1}$. The monsoon circulation is defined using the seasonal variation of the velocity potential in Fig. 8.

Finally, deviation from the zonal and annual mean of velocity potential is shown in Fig. 12. In JJA, the observations show a dominant positive (negative) peak located over East Asia (Pacific and Atlantic oceans). This is a feature of the Northern Hemisphere summer, which includes upper air divergence over East Asia and upper air convergence over the Pacific and Atlantic oceans related to the East Asia summer monsoon. While in winter, lower air divergence and upper air convergence is produced over the same region. This reversal in the pattern between summer and winter quite well explains the monsoon circulation. For summer, the convection center located near the Philippines in the mean velocity potential field in figure 8 can be explained by superposition between one over land associated with the monsoon circulation (Fig. 12) and another near the equator associated with the Walker circulation (Fig. 11). In JJA, CCSM3 underestimates the upper air divergence over East Asia, and splits the peak into two over the eastern Pacific. In DJF, the CCSM3 simulation show an additional peak over Australia compared with observations and the SCoPS simulation. Also, the SCoPS simulation is closer to the observations in terms of intensity than the CCSM3 hindcast. Based on the JJA results, we conclude that the overestimated mean velocity potential in the SCoPS simulation (Fig. 8) is due to the enhanced Hadley circulation (see Fig. 9), and underestimated mean velocity potential in CCSM3 (Fig. 8) is due to the weak simulated monsoon circulation (Fig. 12).

3.3 Seasonal prediction skill

ENSO is the single largest source of interannual variability in the tropics. A good representation of ENSO and its teleconnections are required for regional climate prediction skill on a seasonal time-scale. Figure 13 compares the lead time dependence of the SST anomaly correlation coefficient (ACC) in the Nino 4, 3.4, and 3 regions with the OISST observational dataset for hindcasts initialized in May and November. Overall, the skill of the Nino indices is generally good compared with the persistence curve, although the skill tends to decrease with lead time. SCoPS shows slightly higher skill than CCSM3 over the Nino 4 region in both hindcasts, initialized in May and November. SCoPS shows lower skill than CCSM3 over other regions in the run initialized in May, but higher skill in the run initialized in November, especially

for long lead times.

To examine seasonal prediction skill, the ACC of precipitation and surface temperature between reanalysis data and hindcast anomalies with 3-lead times are calculated for summer and winter (Figs. 14, 15, 16, and 17). Figure 14 shows the correlation coefficients for summer surface temperature anomaly for each modeling system compared to NCEP RA2 data. Only the skills for the first three months after initialization are shown here as the prediction skill quickly diminishes after this in the extra-tropics. Generally, greatest prediction skill for surface temperature is in the tropical belt, especially the ENSO region, with the northern Pacific and equatorial Atlantic also showing high skill in both models. It is remarkable that there is no skill over most continental regions, a common problem in both models. The SCoPS simulation with 1-month lead time shows high prediction skill over most regions compared to that in CCSM3, especially over some continental regions in East Asia which are statistically significant. The ACC skill tends to drop rapidly in the extra-tropics with lead times of 2-months or longer. However, the ACC in SCoPS shows quite a high level over the ENSO region compared to that in CCSM3. The prediction skill of summer precipitation in both hindcasts is generally lower than surface temperature, but it also shows greatest skill over the tropical Pacific (Fig. 15). However, the prediction skill is quite poor in most of the area except for the tropical band, even in the month 1, indicating that the prediction of precipitation is more challenging than that of air temperature. An impressive feature of SCoPS is that it maintains higher ACC skill over the western and equatorial Pacific than CCSM3 for long lead times.

Figures 16 and 17 show the correlation coefficient for winter surface temperature and precipitation from the hindcasts initialized in November. As above, the prediction skill for surface temperature and precipitation is greater over the tropics than the extra-tropics and greater over ocean than land (Kim et al. 2012; Peng et al. 2011). The seasonal prediction skill of CCSM3 and SCoPS is not much different from that of other seasonal prediction systems (e.g., Wang et al. 2009; Kim et al. 2012; Lee et al. 2014). SCoPS shows a similar drop in ACC skill with increasing lead time for surface temperature, however, it shows higher skill over the eastern Indian Ocean, north Pacific, Atlantic Ocean and Northern Hemisphere extra-tropics than CCSM3.

Similarly, the prediction skill of precipitation is lower than that of temperature and shows almost no skill near continental regions. The precipitation ACC in SCoPS shows greater skill than CCSM3 over the western Pacific and tropical band, and some regions of the equatorial Atlantic Ocean for all lead time hindcasts.

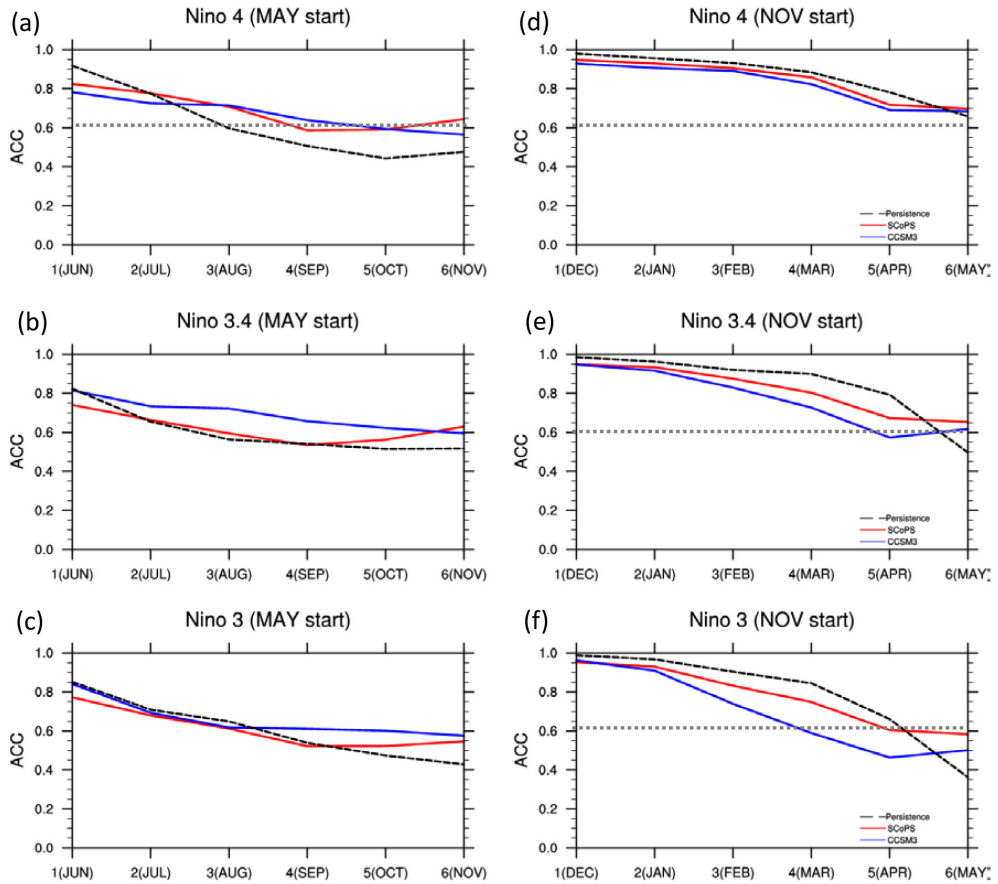


Figure 13 Anomaly correlation coefficients with observations in the Nino4 (top), Nino 3.4 (middle), and Nino 3 (bottom) regions for CCSM3 (blue line) and SCoPS (red line) for varying lead times for starts in: (a), (b), (c), May; and (d), (e), (f) November. The black dashed line indicates the persistence curve for observations.

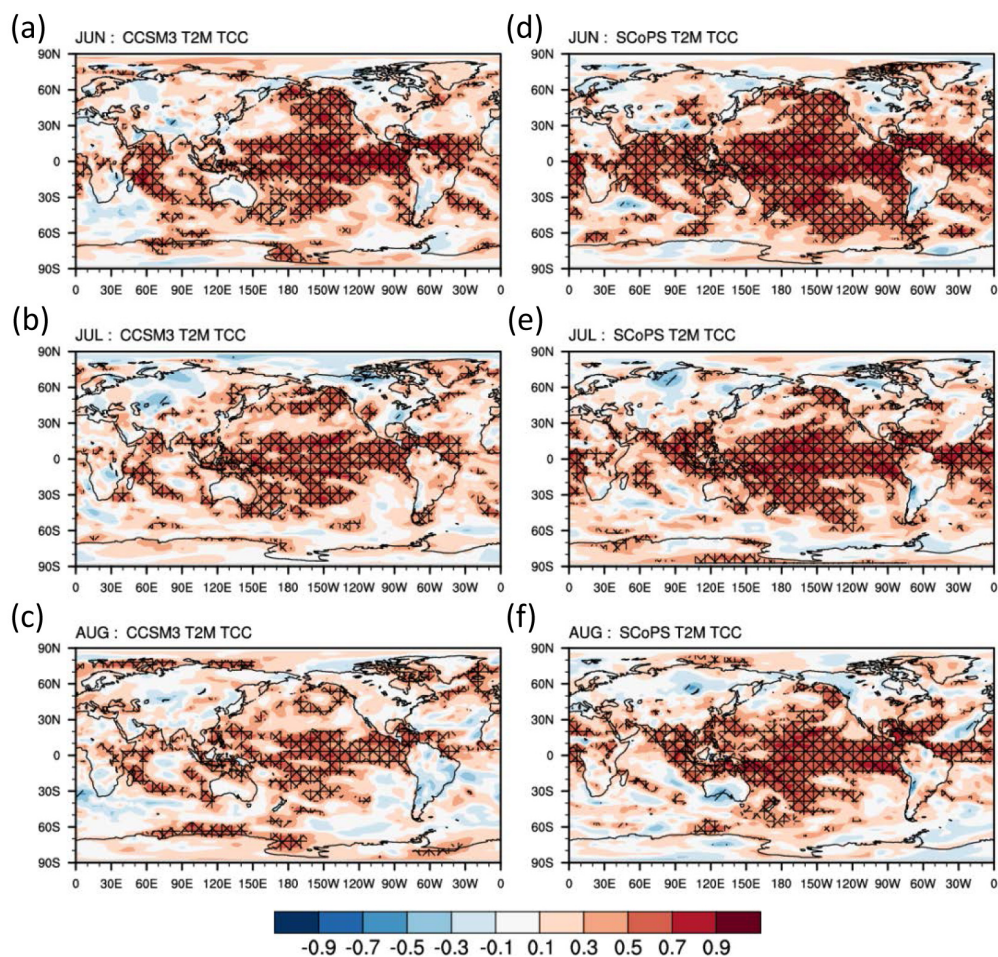


Figure 14 Prediction skill for 2m temperature between reanalysis data and CCSM3 (left) and SCoPS (right) hindcast with a May start. Cross hatching indicates areas that are statistically significant at the 95% level.

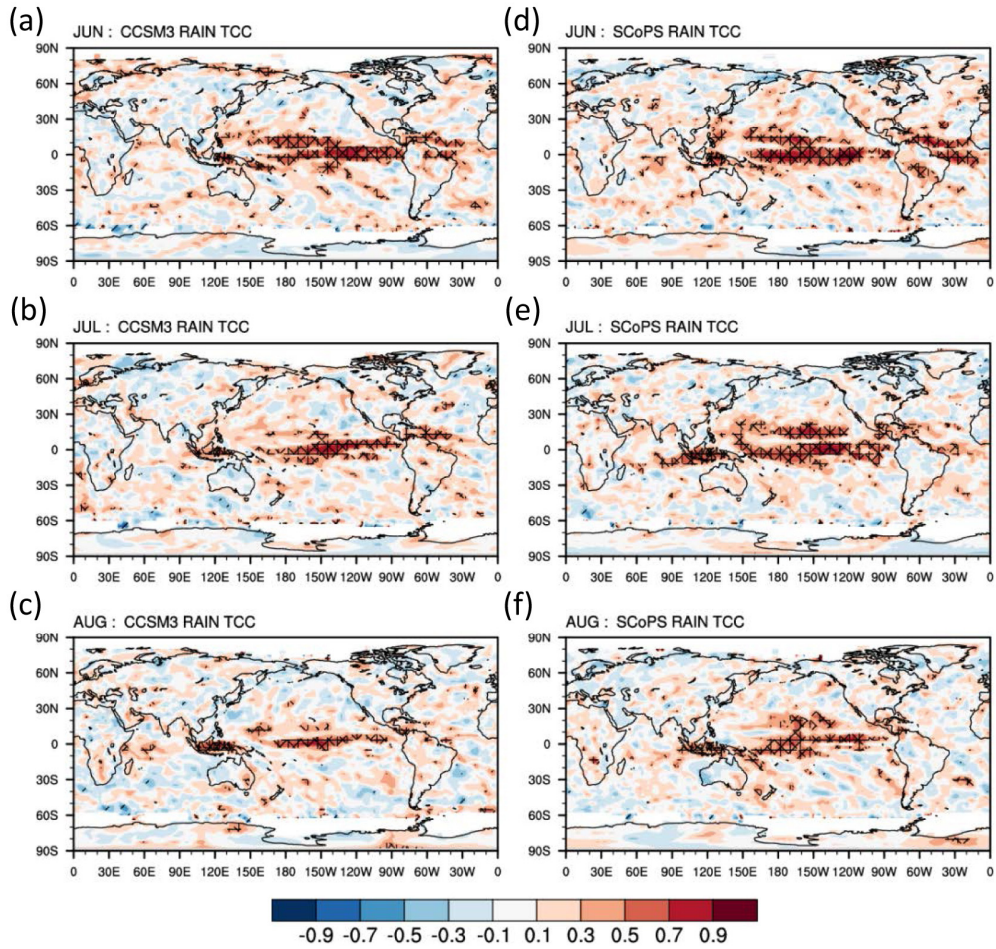


Figure 15 Same as Fig. 14, but for precipitation. GPCP data is used for observations.

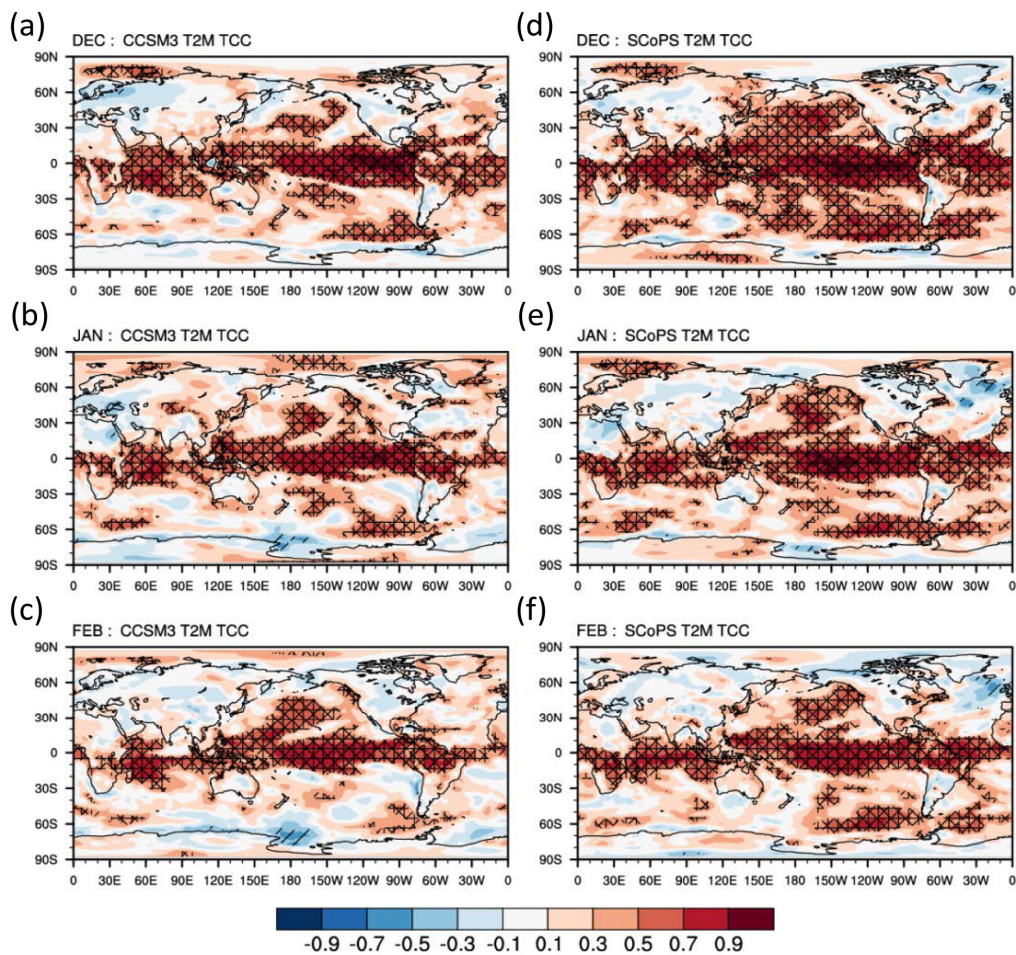


Figure 16 Same as Fig. 14, but for hindcast with a November start.

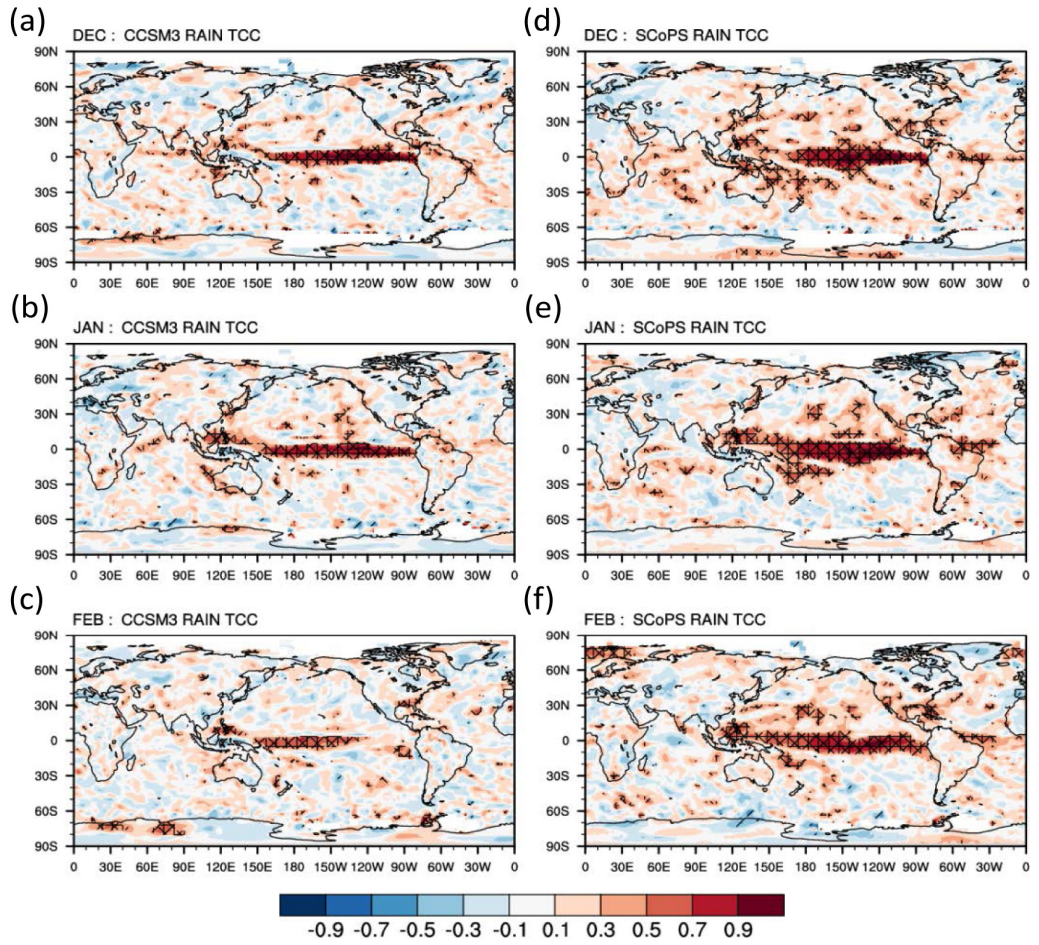


Figure 17 Same as Fig. 15, but for hindcast with a November start.

3.4 East Asia summer monsoon

The capability of CCSM3 and SCoPS in simulating the spatial pattern and interannual variability of the Asian summer monsoon is examined, and several monsoon indices are compared between the both hindcasts and reanalysis data. Figure 18 shows the seasonal-mean precipitation and the 850hPa zonal wind pattern over the South and East Asian region during summer (July–August) in observations (GPCP and APHRODITE for precipitation; ERA-Interim reanalysis for zonal wind) and CCSM3 and SCoPS hindcasts. Note that horizontal resolution of GPCP is $2.5^{\circ} \times 2.5^{\circ}$, while that of APHRODITE is $0.25^{\circ} \times 0.25^{\circ}$ with land-only data. In the climatology for JJA, two major areas of strong precipitation are observed: the intertropical convergence zone over the tropics and the East Asia summer monsoon (EASM) precipitation band extending from southern China to Japan. Local monsoon precipitation maxima are in the north eastern Arabian Sea and the Bay of Bengal, and west of the Philippines. These oceanic regions are the upstream side of low-level monsoon flow before the elevated land surface, coinciding with the convergence area of zonal wind at 850hPa.

CCSM3 reproduces the features well, however, precipitation over the northwestern Pacific is underestimated, and precipitation over the Indian Ocean and western equatorial Pacific tends to be overestimated. Related to this, the low-level monsoon flow pattern is shifted to the precipitation region. The precipitation from SCoPS shows slightly overestimation. Narrow and strong bands of precipitation are indicated over the western areas of India, Indochina, and the Philippines in the high-resolution APHRODITE data. This extremely localized pattern is known to be due to convections generated by narrow mountain areas (Xie et al. 2006; Lee et al. 2013; Ham et al. 2016). The observed pattern is very well represented in the SCoPS hindcast, due to its higher horizontal resolution than CCSM3. Moreover, the SCoPS simulation is remarkably good over China, Korea, and Japan where the seasonal prediction captures the zonally-elongated rain band associated with Changma.

Latitude–time cross sections for the summer precipitation cycle and 850hPa zonal wind at two longitude bands ($70\text{--}80^{\circ}\text{E}$ and $120\text{--}130^{\circ}\text{E}$) are shown in Fig. 19. Because the 3-month prediction skill of the CCSM3 and SCoPS hindcasts is usually used in

seasonal forecasts, four hindcast datasets from runs initialized in February, May, August, and November were synthesized to examine the complete annual cycle of precipitation and wind. Both hindcasts generally well represent the seasonal march of precipitation in the Indian monsoon (70–80°E) and the East Asian monsoon domains (120–130°E) compared to the GPCP and reanalysis data. For example, the northward rain band related to the Indian monsoon during April to July is successfully well represented. However, the CCSM3 simulation shows a weaker peak in the northward propagated rain band as well as strong precipitation over the subtropics and tropics compared to observations. In the SCoPS simulation, the peak of the northward precipitation band and the low-level wind are well captured, although slightly overestimated. However, note that the GPCP observation does not represent orographic heavy rainfall well due to its low resolution. For the East Asian monsoon region, a split rain band is shown during June to August, with one arm over South China Sea, related to the ITCZ, and another over the subtropics, which is related to the Changma front. Both models exhibit the rain peak over the ITCZ well, however, CCSM3 shows exaggerated precipitation over the equatorial rain band, even in winter. In the SCoPS annual cycle, two peak rain seasons are quite well represented, but slightly overestimated. Remarkably, the northward migrated rain band related to the Changma during May to August is also captured by SCoPS.

Figure 20 shows the seasonal-mean precipitation and the 850hPa zonal wind pattern in participating seasonal prediction models in the APCC MME prediction system. Note that the hindcast period for the MME system is 23 years, from 1983–2005. All models well capture the ITCZ and EASM precipitation band as well as the eastward zonal wind from the Indian Ocean to Maritime Continent. The narrow and strong bands of precipitation over western India and the Indochina region are well captured by the IRI, POAMA, and NCEP models due to their high resolution. However, the CWB and NASA models show significantly overestimate precipitation over the southern China and Indian monsoon regions, respectively. The rain band associated with Changma, as seen in observations and the SCoPS simulation, is only shown by POAMA and NCEP. Overall, the precipitation and wind distribution related to the monsoon simulation by SCoPS is more realistic than the CCSM3 simulation as well as almost all MME participating models, suggesting its potential to predict the Asian summer monsoon with a high fidelity.

Meanwhile, the Western North Pacific Subtropical High (WNPSH) is an important driver of Asian summer climate. Figure 21 compares the interannual variability in the 850hPa geopotential height for JJA from RA2 with that from CCSM3 and SCoPS hindcasts initialized in May. SCoPS shows larger variability than CCSM3, bringing it closer to that found in the observational reanalysis data. Figure 21d shows the WNPSH index, which is defined as the normalized anomaly of 850hPa geopotential height for JJA over the region of maximum variability (115–150°E, 15–25°N; Wang et al. 2013), for the hindcast period. The correlation score for this index in SCoPS is 0.81, compared with 0.46 for CCSM3. Note that this improvement cannot be attributed to ensemble size because both models have 10 ensemble members. Summer precipitation over much of East Asia is strongly influenced by the WNPSH (Lu and Dong 2001; MacLachlan et al. 2015). Figure 22a shows the correlation between the WNPSH index from RA2 and precipitation from the GPCP. In the observations, positive correlations are shown over the maritime continental region, Indian Ocean, and Eastern China to Korea and Japan, while negative correlations are shown over equatorial western Pacific. The CCSM3 hindcast well-represents these patterns overall, however, it shows the opposite sign over the Indian Ocean and Korean region. In the SCoPS simulation, the positive correlation over the Indian Ocean and east China to Korea and Japan is well captured, but the negative correlation over the western equatorial Pacific is too weak.

To examine prediction skills for the EASM, this study evaluated two other monsoon indices based on 850hPa wind (Fig. 23). One is that defined by Wang and Fan (1999) as the western Pacific East Asian monsoon index (WPEMI) and the other is defined by Lee et al. (2014) as the East Asian summer monsoon index (EASMI). WPEMI is defined as the 850hPa wind speed anomaly difference between the average of 5–15°N and 100–130°E and that of 20–30°N and 110–140°E. EASMI uses only the 850hPa zonal wind and is defined as the wind anomaly difference between the average of 5–10°N and 130–150°E and that of 25–30°N and 110–130°E. Figure 23 shows the observed WPEMI and EASMI and the predictions by CCSM3 and SCoPS. The predictand is the JJA-mean monsoon indices from the ensemble hindcasts initialized in May. The temporal correlation of WPEMI between the observation and the ensemble mean CCSM3 (SCoPS) prediction is 0.44 (0.69).

In the case of EASMI, both the CCSM3 and SCoPS predictions perform somewhat better than that of WPEMI, with temporal correlations of 0.51 and 0.74, respectively. Based on the results, SCoPS shows a credible prediction of summer monsoon precipitation for this region, with useful levels of skill for East Asia monsoon prediction. To compare the prediction skill of SCoPS for the EASM, the EASMI is plotted with MME participating models for the 23-year period 1983–2005 (Fig. 24). Most of model predictions show useful levels of skill with temporal correlations higher than 0.6, except for the IRI_CA and CWB models. Notably, the POAMA, NASA, and SCoPS predictions perform somewhat better than the other models with correlation coefficients higher than 0.8, with SCoPS having the highest value of 0.824. Based on these results, it is clear that SCoPS is one of the best models for predicting the EASM precipitation pattern of all individual models in the MME prediction system.

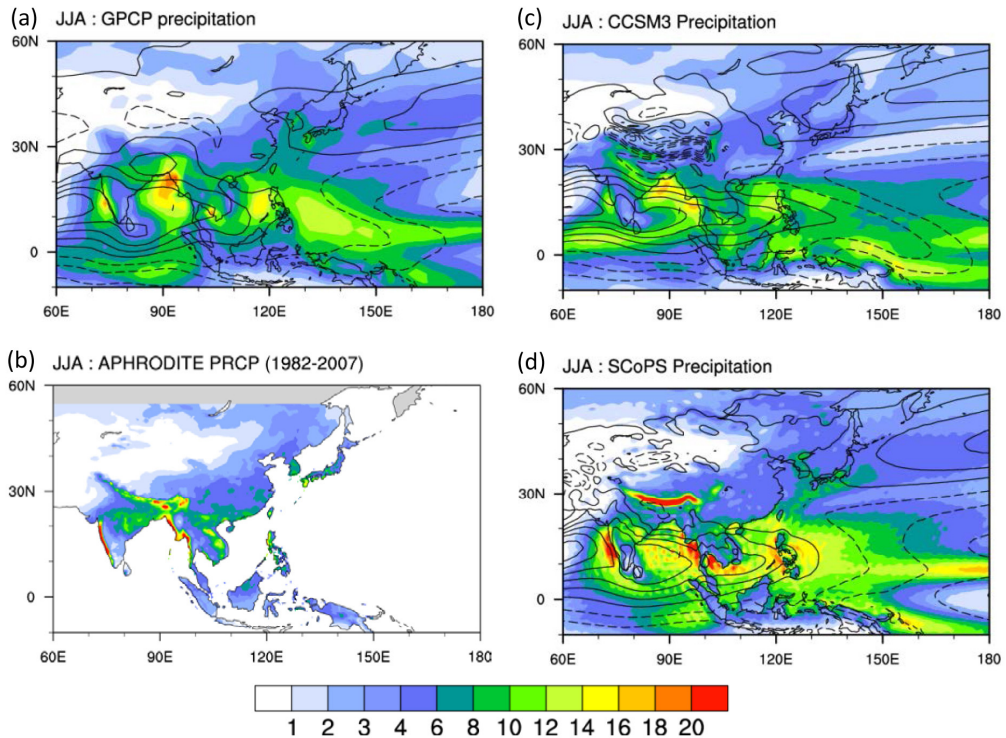


Figure 18. Climatological mean precipitation (shaded) and zonal wind at 850hPa (contour) for June to August averaged over 32 years (1982–2013) from: (a) GPCP and ERA-interim; (b) APHRODITE precipitation; (c) CCSM3; and (d) SCoPS. May is used as the initial month for both hindcasts (3-month lead time).

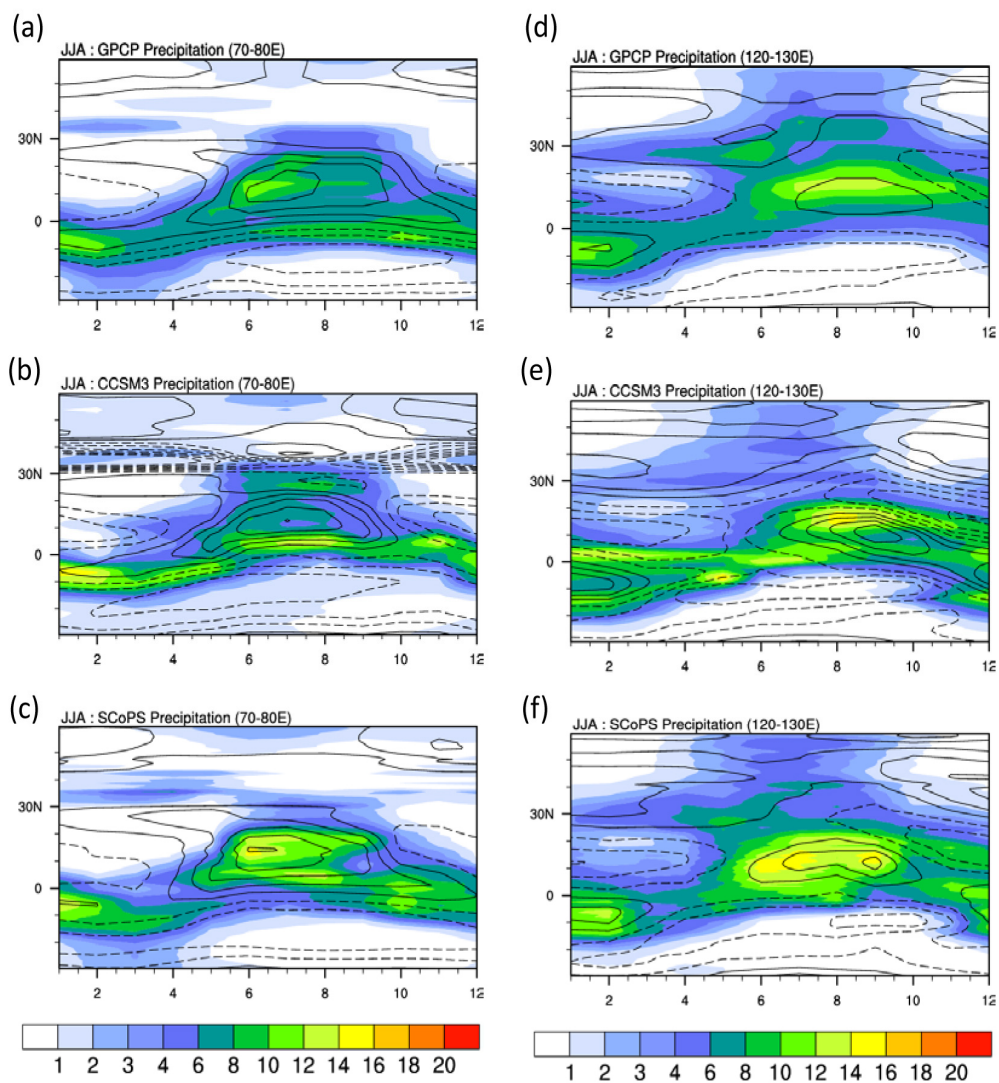


Figure 19 Latitude-time cross section of climatological mean precipitation and 850hPa zonal wind: (a), (b), (c) over the Indian region (70-80°); and (d), (e), (f) over the East Asian region (120-130°). Data from GPCP and ERA-interim (top), CCSM3 (middle), and SCoPS (bottom).

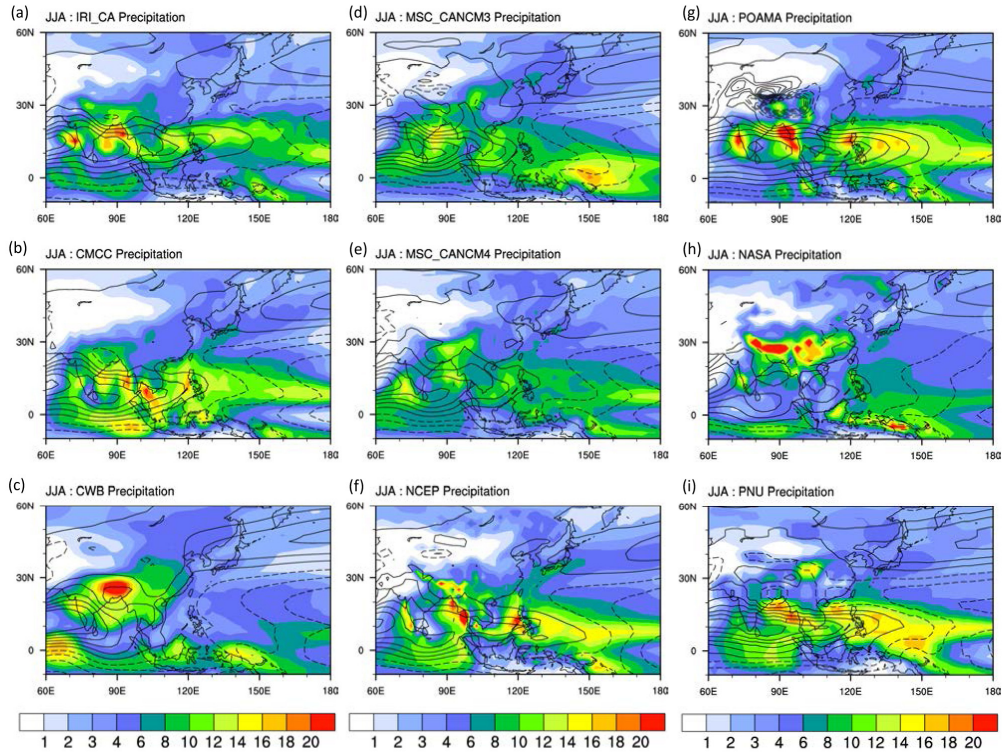


Figure 20 Climatological mean precipitation (shaded) and zonal wind at 850hPa (contour) from individual models used for MME prediction for June-August averaged over 23 years (1983-2005).

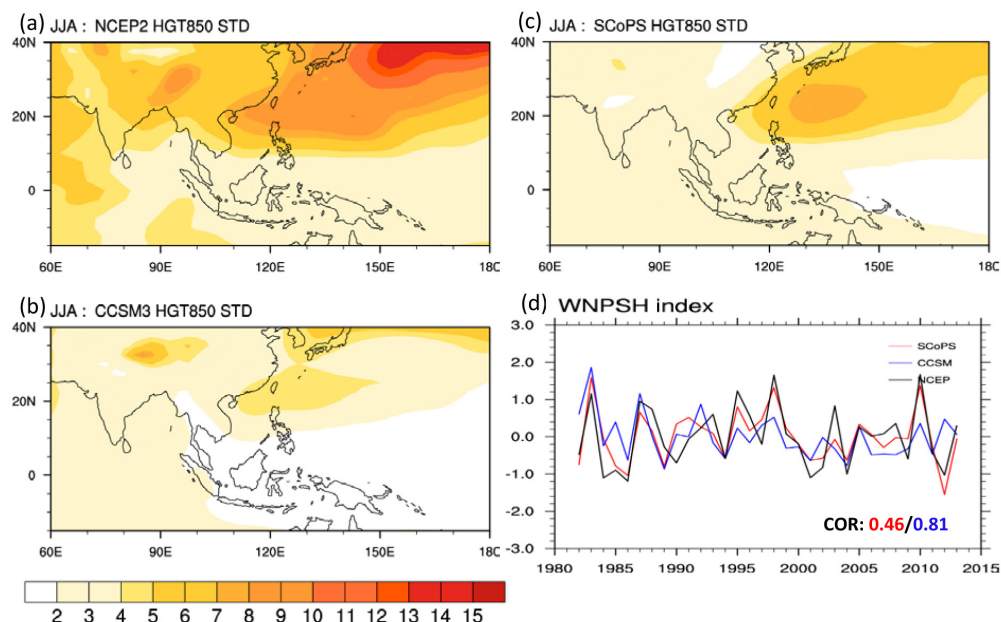


Figure 21 Interannual variability of JJA 850hPa geopotential height for 1982–2013 from: (a) NCEP reanalysis; (b) CCSM3; and (c) SCoPS. (d) The WNP SH index from reanalysis data (black), CCSM3 (blue line), and SCoPS (red line).

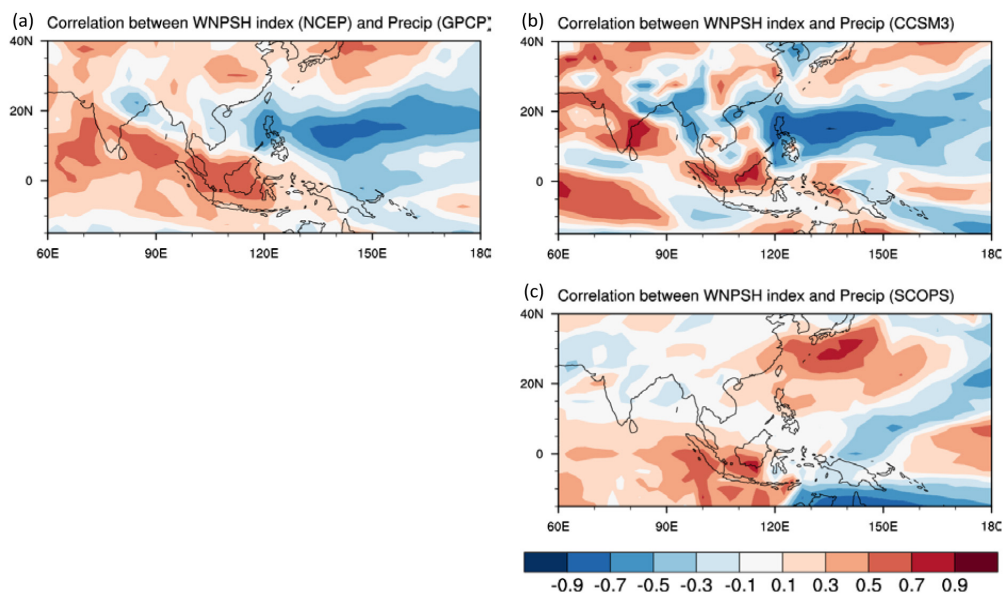


Figure 22 Correlation between the WNP SH index and JJA precipitation from: (a) observations; (b) CCSM3; and (c) SCoPS. For the forecast systems, the correlation is between the ensemble mean WNP SH index and precipitation from individual hindcast members.

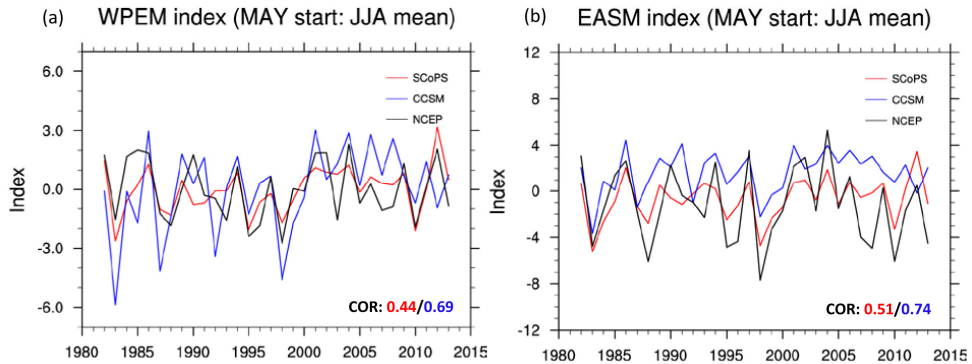


Figure 23 Summer (JJA) (a) WPEMI (Western Pacific East Asian Monsoon Index) and (b) EASM (East Asian Summer Monsoon) indices from observations (NCEP reanalysis data 2), CCSM3, and SCoPS. The WPEMI (Wang and Fan, 1999) is defined as the wind speed anomaly at 850hPa averaged over the region between 5–15°N and 100–130°E minus that over 20–30°N and 110–140°E. EASM is defined as the zonal wind anomaly at 850hPa averaged over the region between 5–10°N and 130–150°E minus that over 25–30°N and 110–130°E.

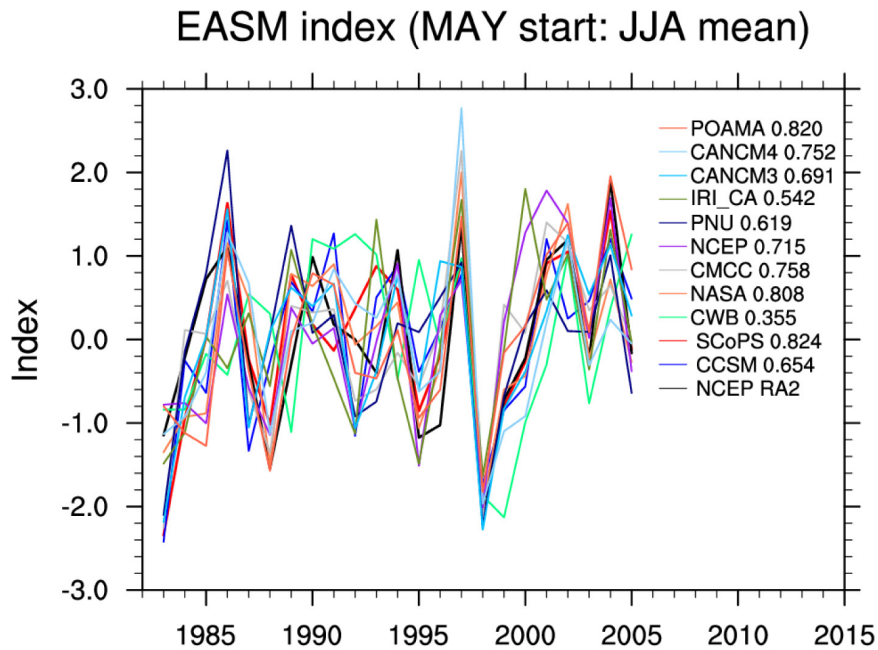


Figure 24 Summer (JJA) EASM (East Asian Summer Monsoon) indices with correlation coefficients from observations (NCEP reanalysis data 2), CCSM3, SCoPS, and individual models for MME prediction. EASM is defined as the zonal wind anomaly at 850hPa averaged over the region between 5–10°N and 130–150°E minus that over the region between 25–30°N and 110–130°E by Lee et al. (2014).

3.5 East Asia winter monsoon

The East Asia winter monsoon (EAWM) is the dominant climate feature over East Asia during the boreal winter. It is The EAWM, which is the strongest winter monsoon of the world, exerts significant impacts on weather and climate inside and outside East Asia (Chen et al. 2005; Zhou et al. 2007; Li and Yang 2010; Jiang et al. 2013). The EAWM consists of subsystems such as the Siberian high, Aleutian low, East Asian trough, low-level northerly wind, and high level East Asian jet stream, and exhibits strong interannual variations. A strong EAWM is characterized by a strong Siberian high, enhanced East Asian jet stream, a deepened East Asian trough, strong northerly flow over East Asia, and frequent cold surges (Ding and Sikka 2006; Park et al. 2011; Jiang et al. 2013). State-of-the-art models show considerable skill in predicting the Asian summer monsoon. However, how well the EAWM can be predicted by climate forecast systems is still not fully known, although a few studies have assessed the predictability of EAWM in different climate models (Kim et al. 2012; Li and Wang 2012; Jiang et al. 2013). In this study, climatological features and interannual variation of the EAWM are compared with observation and reanalysis data to confirm the seasonal prediction skill. Also, the prediction skill for the Arctic Oscillation (AO), which is known as an important feature of seasonal climate variability in East Asia during the boreal winter, is evaluated for the CCSM3 and SCoPS hindcasts initialized in November.

The EASM is a deep system and is associated with various atmospheric features in the entire troposphere. In the lower troposphere, the EASM is associated with the Siberian high and the Aleutian low. These systems result in strong northwesterlies over the eastern flank of the Siberian high, which turn to northeasterlies around 25°N and move southward to the tropics (Fig. 25a). The EAWM is also related to the East Asian trough along the Korea and Japan regions in the middle troposphere and the maximization of the jet stream over southeast Japan in the upper troposphere (Fig. 25d). These features are consistent with Jiang et al. (2013), which used the CFS reanalysis data as the observation dataset. The CCSM3 and SCoPS hindcasts well represent the climatological features related to the EAWM (Figs. 25b, c, e, and f). However, the CCSM3 hindcast shows stronger a Siberian high and Aleutian low, stronger cyclonic circulation in the trough region, and stronger jet stream than

observations (Fig. 26a, c). The SCoPS hindcast also shows some biases, including a weak Siberian high and Aleutian low, however, the maximum jet stream in the upper troposphere and the trough in the middle troposphere are better captured than in CCSM3 (Fig. 26b, d). In addition, the hindcasts have biases in simulating the divergent maritime continental winds compared to observations, with easterlies from CCSM3 and westerlies from SCoPS. The 500hPa geopotential height predicted by CCSM3 is higher than observed except for northeastern China, resulting in a weaker than observed East Asian trough. On the other hand, the SCoPS hindcast shows lower geopotential height than observed except along the Korea and Japan latitude, also resulting in a weaker than observed trough. It is interesting to note that large bias in the 200hPa zonal wind appears over the Indian Ocean in both models. SCoPS generally predicts weaker zonal wind along the westerly jet stream than observed.

The 2-m air temperature over the Asian continent is lower than that over the ocean, with a minimum over the Tibetan Plateau (Figs. 27a, b, c). This temperature pattern is considered as one of the important driving mechanisms of the EAWM (Jiang et al. 2013). During winter, heavy precipitation bands are located over the tropics and the Southern Hemisphere, with a maximum over the Maritime Continent (Figs. 27d, e, f). Most of East Asia shows light precipitation, except the regions from eastern Taiwan to Korea and eastern Japan. Both hindcasts well reproduce the spatial pattern of surface temperature and precipitation, with SCoPS showing more detailed patterns due to its higher resolution than CCSM3. The biases of CCSM3 and SCoPS for surface temperature and precipitation are shown in Fig. 28. CCSM3 shows warm biases over the Tibetan Plateau, eastern Japan, and Maritime Continent, and cold biases along Southern China to Korea and Japan. Conversely, the SCoPS run shows cold biases over Southern China and north of 40°N, and slight warm biases over the Maritime Continent. The cold biases seem to be thermally coupled with the sea level pressure biases. Both models produce more-than-observed precipitation over Japan, the northwestern Pacific, and eastern Maritime Continent, and less-than-observed precipitation over the western Maritime Continent. It is interesting to note that CCSM3 has dry and wet biases over the eastern and western Indian Ocean, respectively, however, the biases are significantly decreased in SCoPS. In addition, the precipitation pattern over the western equatorial Pacific is better

represented in the SCoPS simulation than the CCSM3 run.

The above analysis of hindcasts indicates that both models capture most climatological features of EAWM well. To confirm the prediction skill of the models for interannual variation, the dynamical EAWM index is shown in Fig. 29. This index was proposed by Li and Yang (2010) to measure the interannual variability of the EAWM and is defined as the mean horizontal shear of 200hPa zonal wind:

$$\text{EAWM Index} = (U1 - U2 + U1 - U3)/2, \text{ where}$$

$$U1 = U_{200}(30-35^{\circ}\text{N}/90-160^{\circ}\text{E}),$$

$$U2 = U_{200}(50-60^{\circ}\text{N}/70-170^{\circ}\text{E}), \text{ and}$$

$$U3 = U_{200}(5^{\circ}\text{S}-10^{\circ}\text{N}/90-160^{\circ}\text{E}).$$

Compared to previous indices, the EAWM index accounts for several factors influencing the monsoon (e.g., the Arctic Oscillation and ENSO) and better elucidates the physical processes associated with the EAWM (Li and Yang 2010; Wang and Chen 2010; Wang et al. 2010). CCSM3 and SCoPS predict the observed values realistically in most years, with a correlation coefficient of 0.46 between the observed and predicted indices for SCoPS. However, CCSM3 shows poorer prediction skill than SCoPS, with a correlation coefficient of 0.24 between the observed and predicted indices. We assess the predictability of the EAWM index in SCoPS again, alongside the MME prediction system that has proved to have some skill in simulating EAWM variations (Fig. 30). The EAWM index was best predicted in POAMA, with a temporal correlation coefficient of 0.61, while CMCC and SCoPS rank at 2 and 3 with correlation coefficients of 0.346 and 0.322, respectively. The EAWM index was poorly predicted in CANCM3, NASA, CWB, and CCSM, which have correlation coefficients below 0.1.

The Arctic Oscillation (AO) is known as an important seasonal climate variability in East Asia, especially during boreal winter. It occurs throughout the seasons and is key to explaining year-to-year fluctuations in surface temperature, precipitation, and circulation for many regions across the extratropical Northern Hemisphere. Predictability of the surface AO and its regional Atlantic equivalent, the North Atlantic Oscillation (NAO), on seasonal timescales has until now been very low in dynamical forecast systems, with leading seasonal forecast centers reporting skill levels that

are low and statistically indistinguishable from zero for winter forecasts starting in early November (Johansson 2007; Kim et al. 2012; MacLachlan et al. 2015). Forecasts starting at the onset of winter show slightly more encouraging skill levels, but this includes predictability from initial conditions which affect the first month (Derome et al. 2005). However, the observed relationships hint at the possibility for potentially higher levels of predictability (Cohen and Jones 2011; Folland et al. 2012).

The definition of AO by Thompson and Wallace (1998), which is based on the primary EOF pattern of the monthly mean SLP anomalies during the boreal winter (DJF), was used to examine the prediction skill of both models. The AO index, as a predictand, is defined as the principal component (PC) of the first EOF mode. Figure 31 shows the PC time series from RA2, CCSM3, and SCoPS, for hindcast simulations with a 3-month lead time and November initialization. Both AO PC time series display substantial year-to-year variation. The SCoPS simulation captures the strong negative phase of AO during winter 2009/2010 well. The AAC between the observed and forecast AO index is 0.58 for SCoPS, but only 0.23 for CCSM3. This demonstrates that SCoPS has a significant prediction skill and that CCSM3 is not good for AO simulation. This also explains the increased levels of skill in winter surface temperature and rainfall in the extratropical forecast products from SCoPS. The increased skill of the AO in SCoPS is also accompanied by good reliability for extratropical sea level pressure predictions.

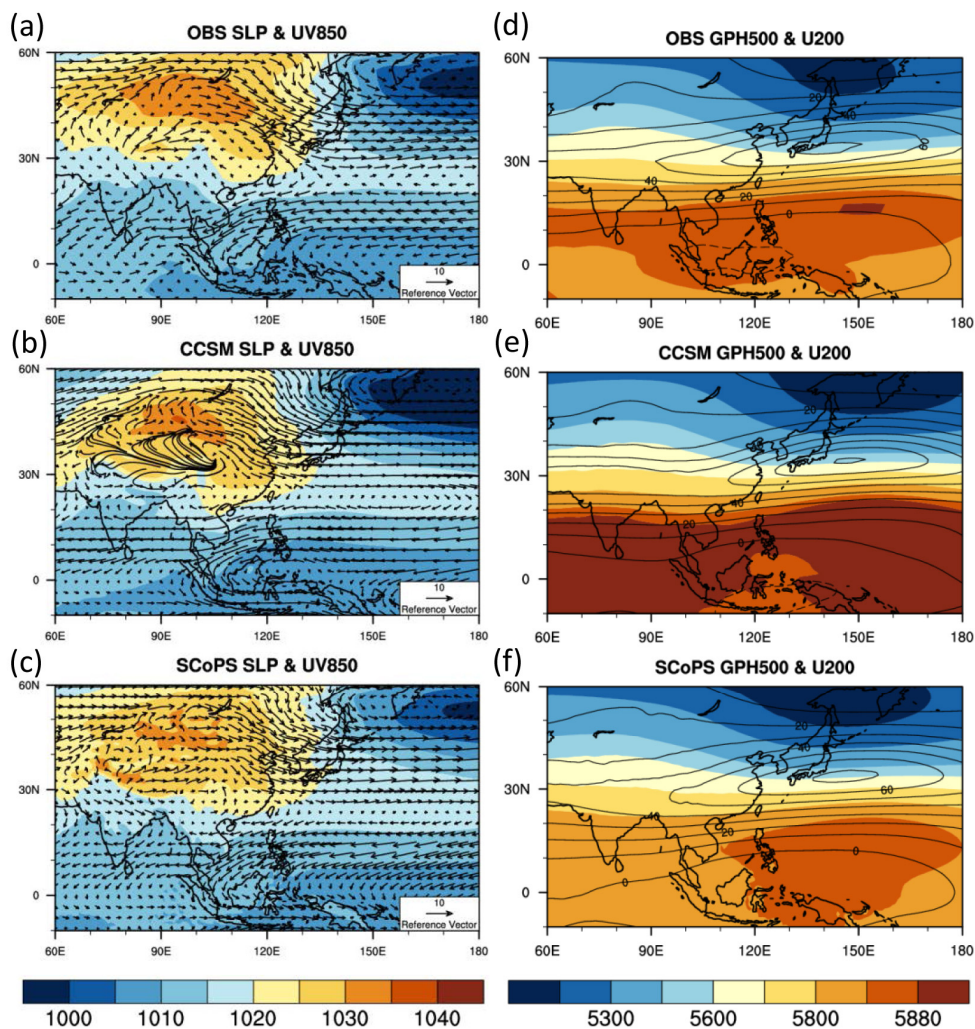


Figure 25 Climatological mean sea level pressure (left; shaded), wind vector at 850hPa (left; contour), geopotential height (right; shaded), and zonal wind at 200hPa (right; contour) from reanalysis data (top), CCSM3 (middle), and SCoPS (bottom) during December to February averaged over 32 years (1982–2013). November is the initial month for both hindcasts (3-month lead time).

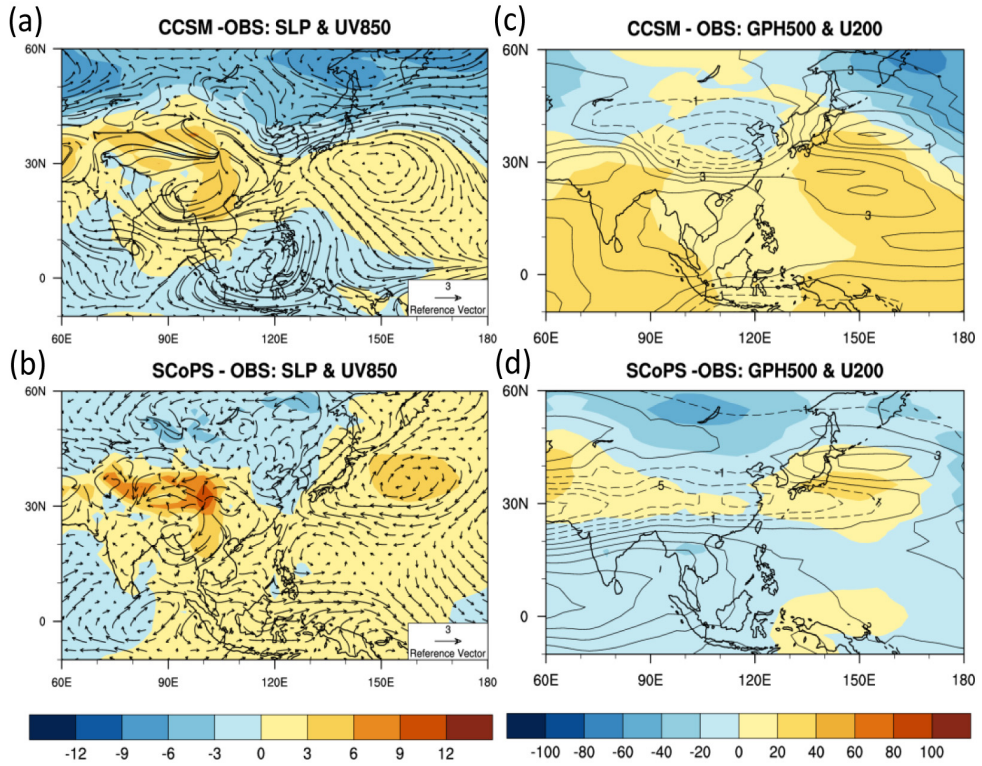


Figure 26 Climatological mean biases of sea level pressure (left; shaded), wind vector at 850hPa (left; contour), geopotential height (right; shaded), and zonal wind at 200hPa (right; contour) from (a), (c) reanalysis data minus CCSM3 (middle), and (b), (d) reanalysis data minus SCoPS during December to February averaged over 32 years (1982–2013). November is the initial month for both hindcasts (3-month lead time).

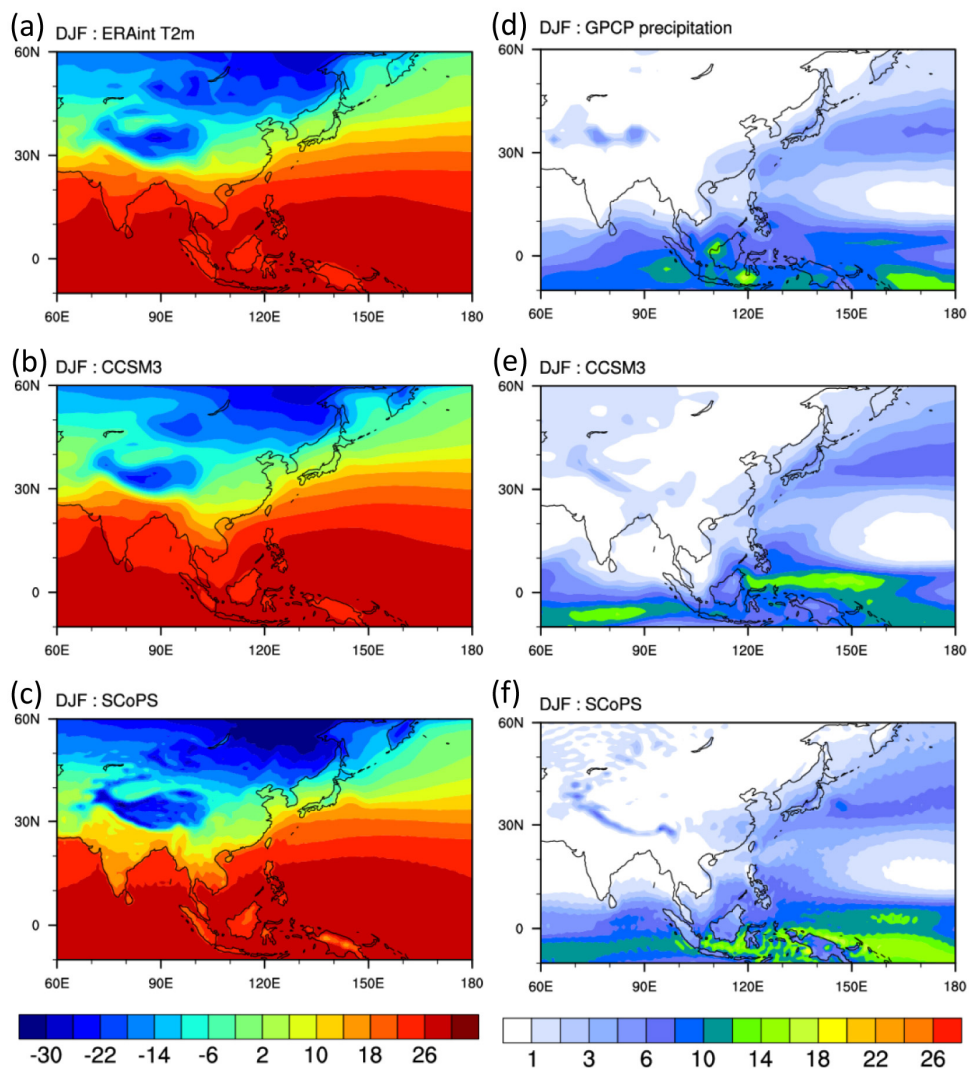


Figure 27 Same as Fig. 23, but for surface temperature (left) and precipitation (right).

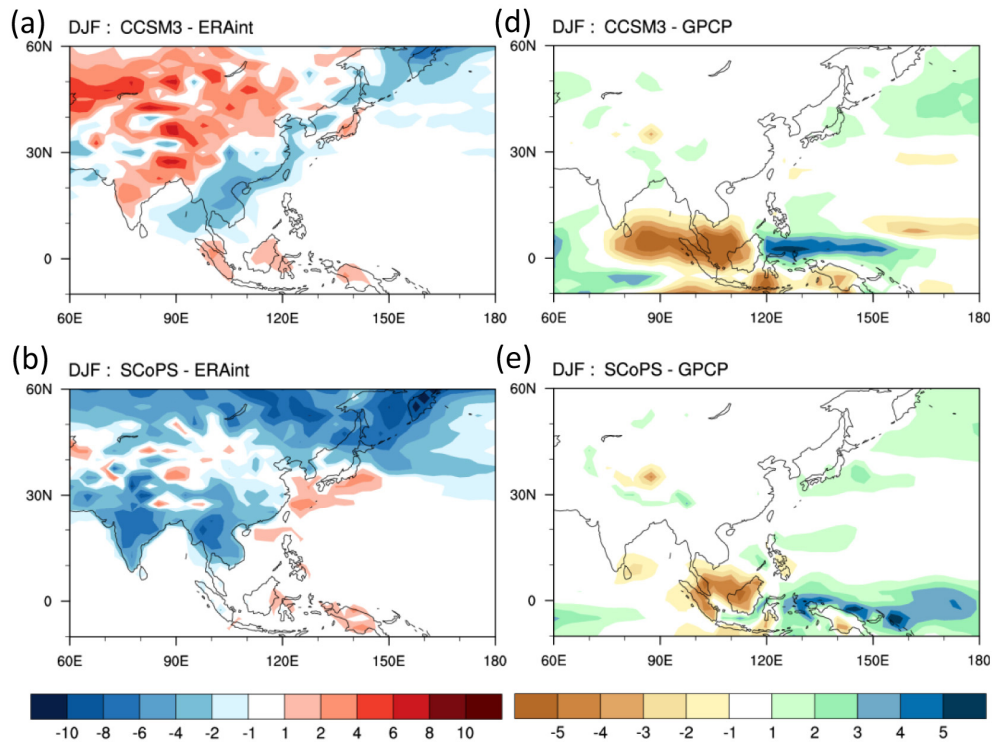


Figure 28 Same as Fig. 23, but for surface temperature (left) and precipitation (right).

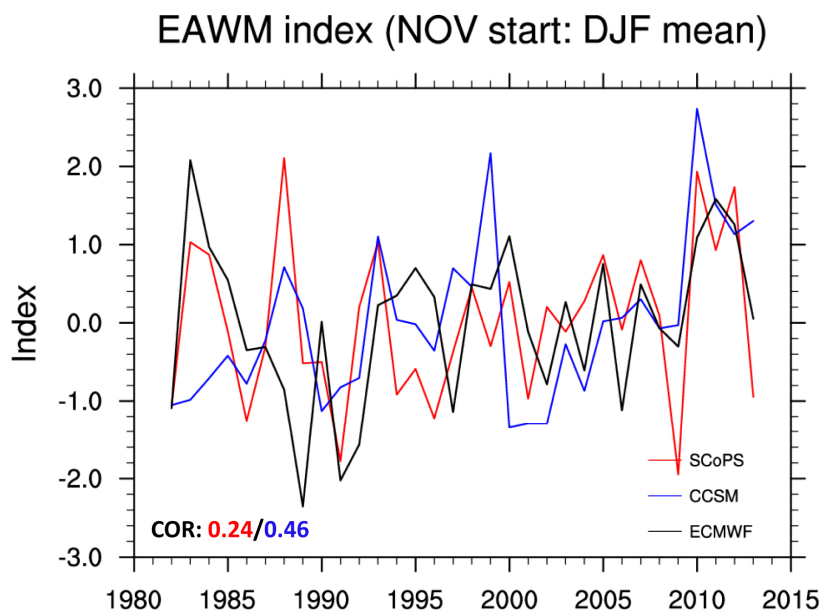


Figure 29 Winter (DJF) EAWM (East Asian winter monsoon) indices from observations (ERA-Interim), CCSM3, and SCoPS. EAWM is defined using the index in Li and Yang (2010).

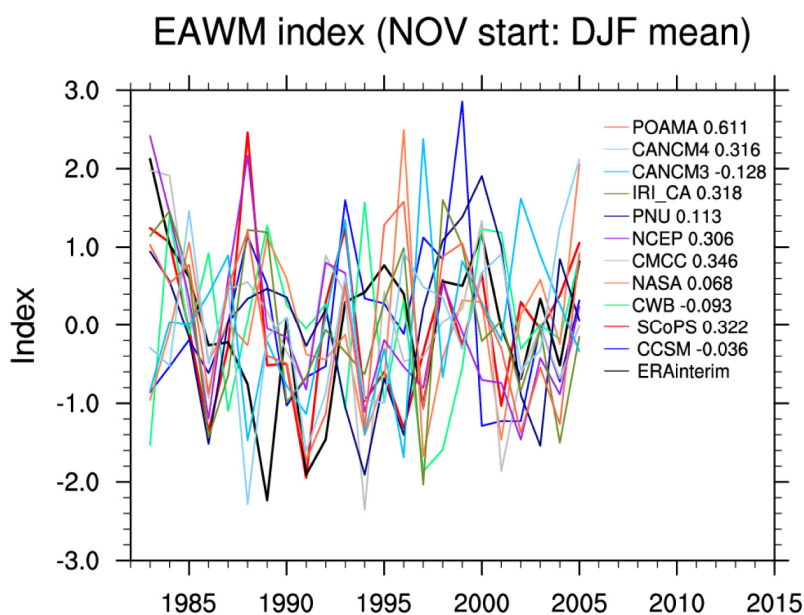


Figure 30 Winter (DJF) EAWM (East Asian winter monsoon) indices from observations (ERA-Interim), CCSM3, SCoPS, and individual models for MME prediction. EAWM is defined using the index in Li and Yang (2010).

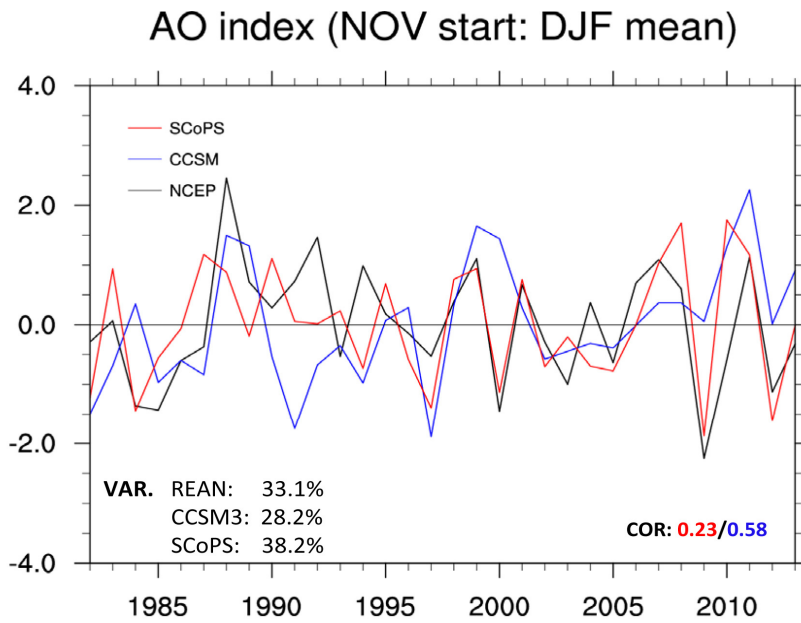


Figure 31 DJF mean normalized AO index from reanalysis (black), CCSM3 (blue), and SCoPS (red). Percentages in the bottom left indicate explained variance (averaged explained variance from each ensemble member) from the pattern. The result is from the CCSM3 and SCoPS hindcast with 3-month lead time.

4. SUMMARY AND CONCLUSIONS

This study evaluated and compared the basic seasonal prediction performance of the APCC in-house CCSM3 and SCoPS seasonal prediction systems using an ensemble hindcast runs over 32 years (1982–2013). The APCC CCSM3 is a global prediction system for seasonal timescales, based on a fully coupled atmosphere, land, ocean, and sea ice model, with nudging of SST data. Each ensemble hindcast run with 10-member ensembles was initialized for SST using GODAS data. The newly developed APCC SCoPS is a state-of-the-art global prediction system for subseasonal to seasonal timescales, based on a fully coupled atmosphere, land, ocean, and sea ice model, with comprehensive initialization processes for atmosphere and ocean. Initialized data for 10-member ensembles is assimilated from NCEP CFS reanalysis and subsurface profile data.

To examine the fidelity of the systems to reproduce and to forecast phenomena, this study focused on three important aspects: systematic biases of hindcast climatology; interannual variability of large-scale circulation; and prediction skill of major climate variability. The first includes the evaluation and identification of systematic biases in the global prediction model, judged from long-term averaged states with many ensembles. The second aspect shows the contributions from the Hadley, Walker, and monsoon circulations in the global divergent field at the upper troposphere, using a seasonal-mean velocity potential field. The third aspect focuses on the prediction skill of ENSO, East Asian summer and winter monsoon, and the AO, which are major drivers of weather and climate variability in East Asia.

The ensemble means for both CCSM3 and SCoPS hindcasts realistically reproduce the gross pattern of the observed climatology for SST, air temperature, and precipitation, although systematic biases are found. Both models show warm biases over the equatorial eastern Pacific, which are lower in SCoPS than CCSM3. However, SCoPS notably reproduces systematic cold bias over the northwestern Pacific. For surface temperature, there are cold biases over North America and warm biases over Eurasia in the SCoPS hindcast, and slight warm biases over Eurasia in the CCSM3 hindcast. In summer, the CCSM3 simulation tends to overestimate rainfall over the equatorial central Pacific and underestimate it over the Atlantic ITCZ

and western Pacific. On the other hand, the SCoPS simulation overestimates precipitation over the central Pacific ITCZ, the Atlantic ITCZ, and maritime continental regions. In winter, the CCSM3 hindcast shows wet biases over the eastern Pacific and western Indian Ocean, and dry biases over the eastern Indian Ocean, while the SCoPS simulation tends to overestimate rainfall over the central Pacific ITCZ, and the western and eastern Pacific.

In this study, tropical large-scale circulations, such as the Hadley, Walker, and monsoon, are separated considering their different driving forces. To analyze the large-scale characteristics of these thermally induced circulations, the upper tropospheric velocity potential is chosen as the suitable parameter. Both hindcast simulations represented the zonal mean velocity potential at 200hPa well, which is the seasonal change of the Hadley circulation, however SCoPS tends to overestimate its intensity. In DJF, the SCoPS simulation plots closer to observations than CCSM3 because the latter has stronger divergent wind. Meanwhile, it is clear that the annual mean component of the zonal deviation fields is a reasonable representation for the Walker circulation. Both simulations very well represent the upward motion in the equatorial western Pacific and downward motion in the eastern Pacific, however, CCSM3 shows stronger intensity on the upward motion. Although SCoPS tends to overestimate the intensity of the Hadley circulation, it provides a reasonable estimate for the Walker circulation. Deviation from the zonal and annual mean of velocity potential, which indicates monsoon circulation, is also evaluated. In JJA, the CCSM3 underestimates the upper air divergence over East Asia, splits its peak into two over the eastern Pacific. Also in DJF, the CCSM3 simulation shows an additional peak over Australia compared with observations and the SCoPS simulation. Also, the intensity of monsoon in the SCoPS simulation is much closer to the observations than that from the CCSM3 hindcast. Based on the JJA results, we infer that the overestimated mean velocity potential from the SCoPS simulation is due to an enhanced Hadley circulation, and underestimated mean velocity potential from CCSM3 is due to a weak simulated monsoon circulation.

To examine seasonal prediction skill, precipitation and surface temperature ACCs between the reanalysis data and hindcast anomalies with 3-month lead time are also evaluated for summer and winter. Generally, surface temperature is best

predicted in the tropical belt, especially the ENSO region. The northern Pacific and equatorial Atlantic also show high skill in both models. The SCoPS simulation with 1-month lead time shows high prediction skill over most regions compared to that of CCSM3. In particular, SCoPS shows more statistically significant skill over continental regions in East Asia than CCSM3.

The capability of CCSM3 and SCoPS in simulating the spatial pattern and interannual variability of the Asian summer and winter monsoon is examined. In the SCoPS annual cycle, the two rain season peaks are quite well represented, but slightly overestimated. Remarkable thing is that northward migrated rain band related to the Changma during May–August is also captured by SCoPS. Overall, precipitation and wind distribution related to the monsoon simulation by SCoPS is more realistic than the CCSM3 simulation, suggesting it has potential to predict the Asian summer monsoon with a high fidelity. In the case of EASM index prediction, which uses a 850hPa wind speed anomaly, CCSM3 and SCoPS predictions show temporal correlations of 0.51 and 0.74, respectively. The results show that the summer monsoon precipitation prediction from SCoPS for this region is credible, with useful levels of skill for prediction of the East Asia Monsoon.

The CCSM3 and SCoPS hindcasts represent climatological features related to the EAWM well. However, the CCSM3 hindcast shows stronger Siberian high and Aleutian low, stronger cyclonic circulation in the trough region, and stronger jet stream than observations. The SCoPS hindcast also shows some biases, including weak Siberian high and Aleutian low, however, the maximum jet stream in the upper troposphere and the trough in the middle troposphere are better captured than in CCSM3. In the case of EAWM index prediction using 200hPa zonal wind, SCoPS shows a correlation coefficient of 0.46 between the observed and predicted indices. However, CCSM3 shows poorer prediction skill than SCoPS, with a correlation coefficient of 0.24 between the observed and predicted indices. Wintertime AO index prediction based on EOF analysis also demonstrates a useful skill in the SCoPS simulation. The ACC between the observed and forecast AO index is 0.58 for SCoPS, but only 0.23 for CCSM3 hindcasts. The increased skill of the AO in SCoPS is also accompanied by good reliability for extratropical sea level pressure predictions. In addition, to compare the prediction skill of SCoPS for EASM and EAWM, the associated

indices are plotted again with MME participating models for the 23 year period from 1983 to 2005. SCoPS EASM predictions perform somewhat better than the other models, with a correlation coefficient higher than 0.8. The EAWM index from SCoPS ranks number 3 among all the models in terms of correlation coefficient. Based on the results, it is clear that SCoPS is one of the best prediction models for the East Asian monsoon system among the individual models in the MME prediction system.

Consequently, this study shows that the overall prediction skill of SCoPS is more realistic than the previous operation version, CCSM3. The better prediction of SCoPS may due to its higher horizontal resolution than CCSM3. Also, the initial condition in SCoPS is better than CCSM3 because SCoPS has integrated atmosphere and ocean initialization, while CCSM3 has only ocean temperature nudging. Furthermore, it is clear that SCoPS has potential to predict the summer precipitation bands related to the East Asian monsoon with a higher fidelity compared to participating models in the MME system. In particular, the summer monsoon index from SCoPS is best, and its EAWM index ranks third, of the 11 individual models in the MME system. However, the systematic biases of land region temperature are marked in SCoPS. It may that the land surface model in SCoPS is too light to capture land-air interactions without initialization for surface variables. Also, it is clear that cold biases in the tropical Pacific are significant. As a result, the SST ACC from SCoPS for the Nino 3 and 3.4 regions is poorer than that of CCSM3. Currently, SCoPS has gone through porting in supercomputing system 4 of KMA, with some debugging errors. This version shows some decrease in SST error and land surface biases. The improved version will be released in the APCC MME prediction system next year. In future studies, improvement processes will be considered to reduce the systematic biases in the tropics, such as physics parameterization, high-resolution vertical layer, and data assimilation for surface variables. Furthermore, to provide physical insights into the differences in prediction skill, it would be useful to assess additional analyses such as interannual variability or teleconnection of climate modes. This will be the subject of future research.

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