The Climatology and Interannual Variability of the East Asian Winter Monsoon in CMIP5 Models

HAINAN GONG
Center for Monsoon System Research, Institute of Atmospheric Physics, Chinese Academy of Sciences, and University of Chinese Academy of Sciences, Beijing, China

LIN WANG AND WEN CHEN
Center for Monsoon System Research, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China

RENGUANG WU
Institute of Space and Earth Information Science, and Shenzhen Research Institute, The Chinese University of Hong Kong, Hong Kong, China

KE WEI
Center for Monsoon System Research, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China

XUEFENG CUI
State Key Laboratory of Earth Surface Processes and Resource Ecology, College of Global Change and Earth System Science, Beijing Normal University, Beijing, China

(Manuscript received 12 January 2013, in final form 17 October 2013)

ABSTRACT

In this paper the model outputs from the Coupled Model Intercomparison Project (CMIP) phase 5 (CMIP5) are used to examine the climatology and interannual variability of the East Asian winter monsoon (EAWM). The multimodel ensemble (MME) is able to reproduce reasonably well the circulation features of the EAWM. The simulated surface air temperature still suffers from a cold bias over East Asia, but this bias is reduced compared with CMIP phase 3 models. The intermodel spread is relatively small for the large-scale circulations, but is large for the lower-tropospheric meridional wind and precipitation along the East Asian coast. The interannual variability of the EAWM-related circulations can be captured by most of the models. A general bias is that the simulated variability is slightly weaker than in the observations. Based on a selected dynamic EAWM index, the patterns of the EAWM-related anomalies are well reproduced in MME although the simulated anomalies are slightly weaker than the observations. One general bias is that the northeasterly anomalies over East Asia cannot be captured to the south of 30°N. This bias may arise both from the inadequacies of the EAWM index and from the ability of models to capture the EAWM-related tropical–extratropical interactions. The ENSO–EAWM relationship is then evaluated and about half of the models can successfully capture the observed ENSO–EAWM relationship, including the significant negative correlation between Niño-3.4 and EAWM indices and the anomalous anticyclone (or cyclone) over the northwestern Pacific. The success of these models is attributed to the reasonable simulation of both ENSO’s spatial structure and its strength of interannual variability.
1. Introduction

The East Asian winter monsoon (EAWM) is an important system in the Northern Hemisphere during boreal winter (Lau and Li 1984; Chang et al. 2006; Huang et al. 2012). It is characterized by the cold Siberian high and the warm Aleutian low at the surface, the low-level northerlies or northeasterlies along the coast of East Asia in the lower troposphere, the East Asian trough in the midtroposphere, and the East Asian jet stream in the upper troposphere (e.g., Chen et al. 2000; Jhun and Lee 2004; Kang et al. 2006; Zeng et al. 2011). The variations of the EAWM can exert large social and economic impacts on densely populated East Asia (Chen et al. 2005; Chang et al. 2006; W. Zhou et al. 2009; Zhou et al. 2011; Huang et al. 2012) and cause the potential occurrence of extreme cold disasters and severe flooding in Southeast Asian countries (e.g., Ding 1994; Chang et al. 2006; Feng et al. 2010; Huang et al. 2012).

The variations of the EAWM are controlled not only by mid- and high-latitude factors such as Eurasian snow cover (Watanabe and Nitta 1999), the Siberian high (Ding and Krishnamurti 1987), the Arctic Oscillation (AO) (Gong et al. 2001; Wu and Wang 2002; Chen and Kang 2006), and blockings over European and Ural regions (Takaya and Nakamura 2005; L. Wang et al. 2010; Cheung et al. 2012), but also by the tropical factors such as El Niño–Southern Oscillation (ENSO) (e.g., Zhang et al. 1996; Wang et al. 2000; Chen et al. 2013) and tropical Indian Ocean sea surface temperature (e.g., Wang and Chen 2014). The EAWM tends to be weak in El Niño years and strong in La Niña years (e.g., Zhang et al. 1997a; Chen et al. 2000). The key system that connects ENSO events and the EAWM is an anomalous anticyclone (cyclone) in the lower troposphere over the western North Pacific and the associated southerly (northerly) wind anomalies (Zhang et al. 1996; Wang et al. 2000).

Numerical climate models are an essential tool to study the monsoon variations and the global climate change. With the development of climate models, the assessment of their simulation capacity becomes an important research subject. Many studies have been carried out to evaluate the capacity of climate system models in representing the regional and global climate (e.g., Giorgi and Mearns 1991; Cox et al. 2000). Compared with other climatic phenomena in the world, simulation of monsoons and their variability has proved to be one of the most challenging problems for climate models (e.g., Webster et al. 1998; Wang et al. 2004). One important reason for the poor simulation of monsoons might be the complicated thermodynamic states induced by the large-scale land–sea thermal contrast (Wang et al. 2001). Another possible reason is the poor capacity of models to produce the correct local anomalous monsoon–ENSO relationship (Wang et al. 2004).

Compared with the assessment of summer monsoons in climate models (e.g., Wang et al. 2004; Kripalani et al. 2007; Lin et al. 2008; T. Zhou et al. 2009), limited studies have been carried out to evaluate the simulations of the EAWM. Ji et al. (1997) analyzed a single atmospheric general circulation model (AGCM) and found that the sea surface temperature (SST) anomalies of the tropical ocean can influence the strength of EAWM significantly. Hu et al. (2000) analyzed a coupled atmosphere–ocean general circulation model (CGCM) and showed that in the global warming scenario, the intensity of the EAWM is likely to weaken while the variances of the EAWM on interannual and interdecadal scales are not affected much. Zhang et al. (1997b) evaluated the representation of the EAWM in eight Atmospheric Model Intercomparison Project (AMIP) models, focusing on the synoptic-scale features of the EAWM such as cold surge. Hori and Ueda (2006) assessed the changes of the EAWM under the influence of global warming in nine CGCMs and found results similar to Hu et al. (2000). These studies either focused on the changes of the EAWM under global warming scenarios or were concerned about the synoptic-scale features of the EAWM. However, the assessment of the climatology and interannual variations of the EAWM in CGCMs was not carried out systematically. Note that the capacity of models in reproducing reasonable climatology and interannual variability of the EAWM is the basis for other EAWM-related researches with models. Therefore, it is necessary to pay more attention to the evaluations of these basic aspects.

Recently, the outputs from the latest climate system models for Coupled Model Intercomparison Project (CMIP) phase 5 (CMIP5) have been released (Taylor et al. 2012). Compared with CMIP phase 3 (CMIP3) models, CMIP5 models have higher resolution (1°–2.8°) and more complete representation of the earth system, including the carbon cycle, dynamic vegetation processes, and so on (Taylor et al. 2012). Based on the outputs from 18 CMIP5 CGCMs, this study will try to address this question: How well do the CMIP5 models reproduce the observed climatology and interannual variability of the EAWM? This question is particularly important because it is the first step for us to investigate the changes of the EAWM in the future. We will also look at the ENSO–EAWM relationship in these models since ENSO is usually regarded as the most important predictor and driving factor for the EAWM variations. Section 2 describes reanalysis datasets, CMIP5 models, and the analysis methods. Section 3 presents the assessments of the climatology and interannual variability of the EAWM as
as well as the ENSO–EAWM relationship in the models. A summary and discussion are given in section 4.

2. Data, model description, and analysis methods

a. Data

In this study, the observational proxies of the atmospheric variables are from the monthly mean 40 yr European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-40) dataset (Uppala et al. 2005) for the period September 1957–August 2002. This dataset has a horizontal resolution of 2.5° × 2.5° and extends from 1000 to 1 hPa with 23 vertical pressure levels. The SST data used here are from the monthly mean Extended Reconstruction of Historical Sea Surface Temperature version 3 (ERSST v3) dataset (Smith et al. 2008). It has a 2° × 2° horizontal resolution and covers the period from January 1854 to the present. The monthly mean Global Precipitation Climatology Project (GPCP) dataset is used as a proxy for rainfall observations (Huffman et al. 2009). This dataset is available on a 2.5° × 2.5° grid starting from January 1979.

b. Model description

The names and expansions of models and related information, including the institutes and horizontal and vertical resolutions, are listed in Table 1. The horizontal

<table>
<thead>
<tr>
<th>Model</th>
<th>Modeling center</th>
<th>Atmosphere resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCC Climate System Model, version 1.1 (BCC-CSM1.1)</td>
<td>Beijing Climate Center (BCC), China Meteorological Administration</td>
<td>128 × 64 L26</td>
</tr>
<tr>
<td>Second Generation Canadian Earth System Model (CanESM2)</td>
<td>Canadian Centre for Climate Modelling and Analysis (CCma)</td>
<td>128 × 64 L35</td>
</tr>
<tr>
<td>Community Climate System Model, version 4 (CCSM4)</td>
<td>National Center for Atmospheric Research (NCAR)</td>
<td>288 × 192 L26</td>
</tr>
<tr>
<td>CNRM Coupled Global Climate Model, version 5 (CNRM-CM5)</td>
<td>Centre National de Recherches Météorologiques (CNRM)/Centre Européen de Recherche et Formation Avancée en Calcul Scientifique</td>
<td>256 × 128 L31</td>
</tr>
<tr>
<td>CSIRO Mark, version 3.6.0 (CSIRO Mk3.6.0)</td>
<td>Commonwealth Scientific and Industrial Research Organization (CSIRO) in collaboration with Queensland Climate Change Centre of Excellence</td>
<td>192 × 96 L18</td>
</tr>
<tr>
<td>Flexible Global Ocean–Atmosphere–Land System Model (FGOALS) gridpoint, version 2 (FGOALS-g2)</td>
<td>State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG), Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University</td>
<td>128 × 60 L26</td>
</tr>
<tr>
<td>FGOALS, second spectral version (FGOALS-s2)</td>
<td>LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences</td>
<td>128 × 108 L26</td>
</tr>
<tr>
<td>GFDL Climate Model, version 3 (GFDL CM3)</td>
<td>National Oceanic and Atmospheric Administration (NOAA) Geophysical Fluid Dynamics Laboratory (GFDL)</td>
<td>144 × 90 L48</td>
</tr>
<tr>
<td>GISS Model E2, coupled with the Hybrid Coordinate Ocean Model (HYCOM) (GISS-E2-H)</td>
<td>National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies (GISS)</td>
<td>144 × 90 L40</td>
</tr>
<tr>
<td>GISS Model E2, coupled with the Russell ocean model (GISS-E2-R)</td>
<td>NASA Goddard Institute for Space Studies</td>
<td>144 × 90 L40</td>
</tr>
<tr>
<td>Hadley Centre Coupled Model, version 3 (HadCM3)</td>
<td>Met Office Hadley Centre</td>
<td>96 × 73 L19</td>
</tr>
<tr>
<td>Hadley Centre Global Environment Model, version 2–Carbon Cycle (HadGEM2-CC)</td>
<td>Met Office Hadley Centre</td>
<td>192 × 144 L60</td>
</tr>
<tr>
<td>INM Coupled Model, version 4 (INM-CM4)</td>
<td>Institute of Numerical Mathematics (INM)</td>
<td>180 × 120 L21</td>
</tr>
<tr>
<td>IPSL Coupled Model, version 5, coupled with Nucleus for European Modelling of the Ocean (NEMO), low resolution (IPSL-CM5A-LR)</td>
<td>Institute Pierre-Simon Laplace (IPSL)</td>
<td>96 × 96 L39</td>
</tr>
<tr>
<td>Model for Interdisciplinary Research on Climate, version 5 (MIROC5)</td>
<td>Center for Climate System Research (The University of Tokyo)</td>
<td>256 × 128 L40</td>
</tr>
<tr>
<td>MPI Earth System Model, low resolution (MPI-ESM-LR)</td>
<td>Max Planck Institute for Meteorology (MPI)</td>
<td>192 × 96 L47</td>
</tr>
<tr>
<td>MRI Coupled Atmosphere–Ocean General Circulation Model, version 3 (MRI CGCM3)</td>
<td>Meteorological Research Institute (MRI)</td>
<td>320 × 160 L48</td>
</tr>
<tr>
<td>Norwegian Earth System Model, version 1 (intermediate resolution) (NorESM1-M)</td>
<td>Norwegian Climate Centre</td>
<td>144 × 96 L26</td>
</tr>
</tbody>
</table>
resolutions of CMIP5 models range from the lowest of $3^\circ \times 2.8^\circ$ (FGOALS-g2) to the finest of $0.94^\circ \times 1.25^\circ$ (CCSM4). The lowest horizontal resolution in the CMIP5 models is much finer than that in the CMIP3 models ($5^\circ \times 4^\circ$), while the finest horizontal resolution in the CMIP5 models is similar to that in CMIP3 models. Monthly mean data from 18 CMIP5 models were downloaded from the website. The historical experiment was employed in this study and only one run was analyzed. The horizontal resolution differs from model to model. To compare with the observations, all the model data were interpolated to match the observations. That is, the atmospheric variables and precipitation were interpolated into $2.5^\circ \times 2.5^\circ$ latitude–longitude resolution to match the ERA-40 reanalysis and GPCP datasets, respectively. The SST data were interpolated into $2^\circ \times 2^\circ$ latitude–longitude resolution to match the ERSST v3 dataset.

c. Analysis methods

In this study, we evaluated the characteristics of the EAWM based on the period 1971–2000, which is the standard period for climatology recommended by the World Meteorological Organization (WMO). In consideration of the availability of GPCP precipitation data, the period from 1979 to 2005 was employed for precipitation analysis. The component of interannual variability was obtained by removing the linear trend from the original data. Seasonal means were considered throughout this paper and they were constructed from the monthly means by averaging the data of December, January, and February (DJF), which results in 30 winters (1971–2000). Here, our convention is that the winter of 1971 refers to the 1970/71 winter. Regression and correlation analysis were used and the significance of the results was evaluated with a two-tailed Student’s $t$ test. The multimodel ensemble (MME) was calculated by simply averaging over the models with equal weighting.

3. Results

a. The climatology

The EAWM is characterized by a strong surface northerly, a strong west–east pressure gradient between the Siberian high and the Aleutian low, an upper tropospheric East Asian jet stream, and a deep longwave trough along the East Asian coastal region (e.g., Chen et al. 2000; Yang et al. 2002; Huang et al. 2012). Therefore, we first evaluate the performances of models in representing these systems. Figure 1 shows the winter mean circulations over East Asia based on the ERA-40 dataset (hereafter referred to as “observations”), MME of 18 CMIP5 models, and their differences. The MME clearly captures the EAWM features near the surface, that is, the lower-tropospheric northerly at the mid-latitudes and the zonal pressure contrast between the Siberian high and the Aleutian low (Figs. 1a,b). Nevertheless, the MME results show some biases (Fig. 1c), such as slightly higher (lower) SLP to the northwest (southeast) of the central Siberian high and weaker northerly wind around the Philippines. The northerly winds along the coast of East Asia, in contrast, are stronger than the observations due to higher SLP over Tibetan Plateau (Fig. 1c). Accordingly, we notice a general cold biases over almost all of East Asia in MME (Fig. 1c) although the center of cold air dome is well captured (Fig. 1b). Compared with the results of the CMIP3 models (e.g., Jiang et al. 2005), the cold biases in the CMIP5 models are much smaller over East Asia, indicating remarkable improvement in the simulations of wintertime surface air temperature. Our preliminary analysis indicates that this improvement is likely accounted for partly by the improvement of the cloud–radiative feedbacks in CMIP5 models. The more detailed descriptions of the land cover change and dynamic vegetation process in CMIP5 models might also contribute to this improvement.

The influence of the Tibetan Plateau on the circulation is clear in the MME with strong circum-plateau westerly flow to the northern and southern flanks of the plateau, and with southward extension of the Siberian high to eastern China to the east flank of the plateau (Figs. 1a,b). In the middle and upper troposphere, the MME generally captures the position and strength of the broad trough along the East Asian coast and the jet stream over East Asia (Figs. 1d,e). Nevertheless, obvious negative biases can be observed in the 500-hPa geopotential height over the whole domain shown in Fig. 1f. This negative bias is especially strong over the climatological East Asian trough region, indicating a deeper East Asian trough in MME than that in the observations (Fig. 1f). Hence, the north–south geopotential height gradient is overestimated in MME, which in turn leads to a slightly stronger westerly jet stream in MME than that in the observations.

To delineate the performances of the 18 models in representing the EAWM climatology in more detail, Taylor diagrams (Fig. 2) are plotted for the typical area of East Asia ($20^\circ–50^\circ$N, $100^\circ–145^\circ$E), which was used before in Boo et al. (2011). The same region is applied to selected variables including sea level pressure (SLP), surface air temperature (SAT), precipitation (Pr), geopotential height at 500 hPa ($Z_{500}$), zonal wind at 200 hPa (U200), and meridional wind at 850 hPa (V850). The SAT, U200, and Z500 have high pattern correlations with the
FIG. 1. Climatology (1971–2000) of winter (DJF) mean (a) 850-hPa winds (vectors, m s\(^{-1}\)), sea level pressure [contours, contour interval (CI) = 5 hPa], and surface air temperature (shading, °C) (d) The 500-hPa geopotential height (contours, CI = 50 gpm) and 200-hPa zonal wind (shading, m s\(^{-1}\)) based on ERA-40 reanalysis data. (b),(e) As in (a),(d), but for the MME of the 18 CMIP5 models. (c) Differences between (b) and (a) (CI = 1 hPa). (f) Differences between (e) and (d) (CI = 10 gpm).
observations. Most of the corresponding correlation coefficients exceed 0.95 and the intermodel spread is small. In contrast, the pattern correlations for Pr and V850 are relatively lower, most of which are below 0.9. Although this value is acceptable, the intermodel spreads for Pr and V850 are much larger (Figs. 2a,b). The standard deviations of the simulated SAT and Z500 are almost identical to those in the observations with very small intermodel spread, while those of the simulated Pr and V850 in most models are clearly greater compared to the observations. These results suggest that the capacity of simulation depends not only on the model but also on the variable, and that the large-scale circulations are more easily captured by the model.

The Taylor diagram can reflect the resemblance of the spatial pattern but cannot describe the absolute intensity of the variables, so we further examine the intensity of several systems that are closely related to the EAWM (Table 2) via calculating the differences between models and observations. The biases of the Siberian high (Fig. 3a) and the Aleutian low (Fig. 3b) in MME are $-1.2$ and $-0.9$ hPa, respectively. This result suggests that the MME of CMIP5 model is good at describing the SLP field related to the EAWM. It also implies that the MME is better than almost all the single models in simulating the SLP climatology since the biases of MME are smaller than that of most of single models (Figs. 3a,b). Figures 3c and 3d display the biases of near-surface (10 m) meridional wind and the 850-hPa wind speed over East Asia, respectively. The MME captures the magnitude of meridional wind successfully but overestimates the magnitude of wind velocity, with a positive bias about $0.5 \text{ m s}^{-1}$. This bias is similar to that in AMIP models (Boo et al. 2011), implying not much improvement of CMIP5 models in this aspect. For the 500-hPa trough over East Asia (Fig. 3e), almost all the models have a strong negative bias (the MME bias is about $-39 \text{ gpm}$). It indicates that the climatological strength of the East Asian trough is overestimated by most of the models. This overestimation matches that of the 850-hPa wind speed index.

**Table 2. The parameters used for EAWM evaluation.**

<table>
<thead>
<tr>
<th>Name</th>
<th>Reference</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{SH}$</td>
<td>Chang et al. 2006</td>
<td>SLP ($40^\circ$–$60^\circ$N, $70^\circ$–$120^\circ$E)</td>
</tr>
<tr>
<td>$I_{NP}$</td>
<td>Trenberth and Hurrell 1994</td>
<td>SLP ($30^\circ$–$65^\circ$N, $160^\circ$–$140^\circ$W)</td>
</tr>
<tr>
<td>$I_{V}$</td>
<td>Chen et al. 2000</td>
<td>Meridional wind, 10 m ($10^\circ$–$25^\circ$N, $110^\circ$–$130^\circ$E and $25^\circ$–$40^\circ$N, $120^\circ$–$140^\circ$E)</td>
</tr>
<tr>
<td>$I_{UV}$</td>
<td>Boo et al. 2011</td>
<td>Amplitude of 850-hPa wind vector ($30^\circ$–$50^\circ$N, $120^\circ$–$140^\circ$E)</td>
</tr>
<tr>
<td>$I_{TROUGH}$</td>
<td>Sun and Li 1997</td>
<td>Z500 ($30^\circ$–$45^\circ$N, $125^\circ$–$145^\circ$E)</td>
</tr>
<tr>
<td>$I_{JET}$</td>
<td>Yang et al. 2002</td>
<td>U200 ($30^\circ$–$35^\circ$N, $130^\circ$–$160^\circ$E)</td>
</tr>
</tbody>
</table>
The strength of the 200-hPa East Asian jet stream is well reproduced in the MME (Fig. 3f) but is seriously underestimated (overestimated) in FGOALS-s2 (IPSL-CM5A-LR).

Figure 4 shows the intermodel spreads estimated with the standard deviation among 18 models. The intermodel spreads of SLP (Fig. 4a) are small over East Asia but are large over high latitudes, especially over the North Pacific and to the north of the Tibetan Plateau. It reflects that the simulations of the Aleutian low and the Siberian high vary largely among models, the latter of which might be due to the treatment of the topography of the Tibetan Plateau. Accordingly, the spreads of SAT and V850 are very large over East Asia and northeastern Asia (Figs. 4b,d) since these two variables are closely associated with the east–west pressure contrast between the Siberian high and the Aleutian low. The intermodel spreads of 850-hPa zonal wind (U850) and U200 are large over the North Pacific, straddling the corresponding wind speed maximum (Figs. 4c,f). It indicates
that the locations of the zonal wind maximum and their intensities vary among models. The magnitudes of the U850 spreads are smaller than those in CMIP3 models (Hori and Ueda 2006), suggesting some improvement of CMIP5 models in this aspect. The intermodel spread of Z500 is large over the northern Pacific and smaller near the East Asian trough region (Fig. 4e).

b. The interannual variability

In this section, we use the interannual standard deviation of meteorological parameters as a metric to describe the intensity of interannual variability associated with the EAWM. Figure 5 shows the interannual standard deviations of winter mean V850 (shading) and SLP (contours) in 18 models. The results based on reanalysis data are also given for comparison. The interannual variability of V850 is large over southern China, the South China Sea, and the neighboring western North Pacific (Fig. 5t), which is related to the anomalous anticyclone (cyclone) around the Philippine Sea that usually establishes during El Niño (La Niña) developing years and influences the EAWM (Wang et al. 2000). Most of the models display large interannual variability of V850 in these regions. The simulated variability is evidently smaller in five models (GISS-E2-H, GISS-E2-R, HadGEM2-CC, INM-CM4, and IPSL-CM5A-LR) and much larger in two models (FGOALS-s2 and MIROC5) than in the observations. Besides, almost all models can capture the large variability of SLP around the Aleutian low over the North Pacific and the relatively smaller variability of SLP around the Siberian high. The MME reproduces well the patterns of variability for V850 and SLP (Figs. 5s,t).

Figure 6 shows the interannual standard deviations of winter mean SAT (contours) and precipitation (shading) over East Asia and the western Pacific. Here, the variability of precipitation extending to 20°S is also assessed because the EAWM-related cold surge can cause anomalous convective precipitation over the Maritime Continent (e.g., Chang et al. 2006; Wang and Chen 2010). The standard deviation of observed SAT is very large at high latitudes and decreases southeastward to
eastern China (Fig. 6t). This feature is well captured by all the models as well as by the MME (Figs. 6a–s). The precipitation variability is large over the Maritime Continent (Fig. 6t). The MME captures well the large variability in this region. The INM-CM4 model underestimates the variability of precipitation, while about half the CMIP5 models overestimate the variability, particularly over the Maritime Continent. The magnitude of the precipitation variability over Maritime Continent is quite consistent with that of V850 (Fig. 5, shading). This implies that the models may capture the excitation of the precipitation anomalies over the Maritime Continent by EAWM-related northerly wind anomalies to some extent.

Figure 7 presents the interannual standard deviation of winter mean U200 (shading) and Z500 (contours). In the observations, the largest interannual standard deviation of U200 is located in the tropics and subtropics of the central-eastern Pacific (Fig. 7t), which is associated with ENSO (Yang et al. 2002). There are two regions of relatively large variability of U200 over Asia. One extends from central China eastward to the North Pacific and the other is located over the South China Sea and Southeast Asia (Fig. 7t). Almost all the models roughly
reproduce the relatively large variability in the above two regions over East Asia and the ENSO-related strong variability over the tropical and subtropical central-eastern Pacific. Four models (GISS-E2-H, GISS-E2-R, INM-CM4, and MRI CGCM3) underestimate while two models (FGOALS-s2 and CCSM4) overestimate the U200 variability over tropics and subtropics of the central-eastern Pacific. These results imply that the models have some capability in simulating ENSO-related atmospheric circulation. The large variability of Z500 over the North Pacific can be captured by the MME, but is not well reproduced in several models including FGOALS-s2, HadCM3, INM-CM4, MPI-ESM-LR, and MRI CGCM3. Figure 8 further shows the amplitudes of interannual variability for the six selected parameters that are closely related to the EAWM (Table 2). The ratio of MME variability to the observed variability ranges from 0.79 to 0.97 for the six parameters. The magnitudes of variability of the Siberian high, the Aleutian low, and 850-hPa wind speed over East Asia in MME are almost identical to those in the observations (Fig. 8). This result implies that the Siberian high or SLP gradient associated with the EAWM may be a good choice when we measure the interannual variability of the EAWM in CMIP5 models.

Besides the strength and spatial pattern of the interannual standard deviation, it is essential to assess the EAWM-related circulation anomalies revealed by the EAWM index in models. Compared to the summer monsoon, depiction of the variability of the winter monsoon is less sensitive to the indices chosen. Jiang et al. (2013) suggested that the Li and Yang (2010) index is perhaps the index that can describe most features and physical processes associated with EAWM.
Hence, we choose the Li and Yang (2010) index that represents the mean wind shears based on three bands of U200. The definition of the EAWM index is as follows:

\[
\text{EAWMI} = \frac{\left( \frac{\left[ U_{200}(30^\circ-35^\circ N, 90^\circ-160^\circ E) \right]}{\left[ U_{200}(5^\circ-10^\circ N, 90^\circ-160^\circ E) \right]} - \frac{U_{200}(50^\circ-60^\circ N, 70^\circ-170^\circ E)}{U_{200}(5^\circ-10^\circ N, 90^\circ-160^\circ E)} \right)}{2.0},
\]

where \( U_{200} \) denotes 200-hPa zonal wind.

Figure 9 shows the circulation anomalies regressed onto the normalized EAWM index in MME and observations. In the observations, positive EAWM index (strong EAWM) is associated with below-normal SAT over East Asia, above-normal SLP over Mongolia and Siberia, and below-normal SLP over the North Pacific (Fig. 9a). The structure of SLP anomalies matches the northerly anomalies along the coast of East Asia (Fig. 9a). The MME captures the EAWM index-related SAT and SLP anomalies quite well, although the simulated SLP anomalies are somewhat weaker than the observations over the North Pacific (Fig. 9b). It should be noted that the EAWM index-related winds anomalies are weaker in MME than in the observations. One prominent bias is that the MME failed to reproduce the northeasterly anomalies to the south of 30\(^\circ\)N (Fig. 9b). A further inspection reveals that only three models (CNRM-CM5, GFDL CM3, and MIROC5) can reproduce the northeasterly anomalies in subtropical East Asia (not shown). In fact, this prominent bias always exists if we choose other indices listed in Wang and Chen (2010). The magnitude of this bias can be significantly reduced if the EAWM indices based on low-level wind (e.g., Chen et al. 2000; Yang et al. 2002) are employed. Hence, these results suggest that this general bias in lower-tropospheric northerly wind is partly related to the choice of the EAWM index and partly due to the inadequacy of...
reproducing the EAWM-related tropical–extratropical interactions in models.

In the middle and upper troposphere, the observations reveal negative $Z_{500}$ anomalies over East Asia and the North Pacific and positive $U_{200}$ anomalies along the climatological East Asian jet stream (Fig. 9c), indicating an deepened East Asian trough and an accelerated East Asian westerly jet stream in strong EAWM winters, which are consistent with previous results (e.g., Jhun and Lee 2004; Chen et al. 2005; Wang et al. 2009). The MME reproduces these two features very well although the $Z_{500}$ and $U_{200}$ anomalies are relatively weaker over East Asia and the North Pacific (Fig. 9d).

c. ENSO–EAWM relationship

ENSO exerts great influence on the global climate as well as on the interannual variations of the EAWM (e.g., Huang et al. 2012) via an anomalous low-level anticyclone (cyclone) located over the western North Pacific (Zhang et al. 1996; Wang et al. 2000). In this section, we will evaluate the ENSO–EAWM relationship in the 18 CMIP5 models. First, we choose an EAWM index that can reflect the ENSO–EAWM relationship tightly. Wang and Chen (2010) provided a comprehensive assessment of the existing EAWM indices. They reported that the EAWM indices based on lower-tropospheric or near-surface meridional wind speed reflect the ENSO–EAWM relationship better than other indices on the interannual time scale. Based on their evaluation, we choose the EAWM index defined by Chen et al. (2000) that uses the mean of area-weighted near-surface meridional wind over the east coast of China ($10^\circ$-$25^\circ$N, $110^\circ$-$130^\circ$E and $25^\circ$-$40^\circ$N, $120^\circ$-$140^\circ$E). The sign of the EAWM index is reversed so that the positive (negative) sign of the index corresponds to a strong (weak) EAWM. Because of the lack of near-surface wind data in FGOALS-g2 and CCSM4 models, we only analyze the results based on the 16 remaining models.

Table 3 lists the correlation coefficients between the EAWM index and the Niño-3.4 index both in models and in observations as well as the standard deviations of the EAWM and Niño-3.4 indices. The observed correlation coefficient between EAWM and Niño-3.4 indices is $-0.71$. Almost all the models obtain a negative correlation between EAWM and ENSO. One exception is the MRI CGCM3 model, which shows a positive correlation coefficient of 0.08. The correlation coefficient exceeds 95% confidence level in three models (BCC-CSM1.1, CanESM2, and HadCM3) and exceeds 99% confidence level in seven models (CNRM-CM5, CSIRO Mk3.6.0, FGOALS-s2, GFDL CM3, MIROC5, MIROC5, and NorESM1-M).

What are the possible factors that influence the relationship between ENSO and EAWM? First, we compare the spatial structures of ENSO-related SST anomalies in the models with those in observations. Figure 10 shows winter mean SST anomalies regressed onto the simultaneous normalized Niño-3.4 index. In observations, positive SST anomalies are seen in the tropical central and eastern Pacific (Fig. 10r). The SST anomalies in CMIP5 models are generally confined within 10° in latitude from the equator (also in MME) but vary both in the amplitude and in the longitudinal location and extension (Figs. 10a–q). Especially, the ENSO-related SST anomalies in four models (GISS-E2-H, GISS-E2-R, INM-CM4, and MRI CGCM3) are tightly confined in the Niño-3.4 region and are much weaker than those in both the observations and the rest of models. In addition, it is noteworthy that the CSIRO Mk3.6.0 model does not reproduce a reasonable ENSO-related SST pattern, with the maximum SST anomalies being located in the tropical western Pacific (Fig. 10d). This bias in the CSIRO Mk3.6.0 model was reported by Kim and Yu (2012). Interestingly, we notice that the models that show poor spatial patterns of SST anomalies also display a weak ENSO–EAWM relationship. This implies that the capacity of models in representing the SST pattern of ENSO may influence the ENSO–EAWM relationship. Besides, we notice that the representations of ENSO–EAWM relationship in models may be affected by the temporal variability of ENSO. The interannual standard deviation of Niño-3.4 index is 1.16 in the observations. A comparable value (exceeding 0.9) is obtained in 8 out of 10 models that capture the ENSO–EAWM relationship, while a smaller value (all below 0.8) is observed in the six models that do not capture the ENSO–EAWM relationship (Table 3). The interannual standard deviation of the EAWM index, in contrast, does not reveal a clear association with the performance of the ENSO–EAWM relationship in
CMIP5 models. These results suggest that the representation of the ENSO–EAWM relationship in CMIP5 models depends partly on the spatial structure of ENSO and partly on the strength of interannual variability of ENSO.

To further demonstrate the above hypothesis, the 16 CMIP5 models were divided into two groups based on two criteria: 1) the number of grids whose value is above 0.6 K in the tropical Pacific (8°S–8°N, 180°–110°W) in Fig. 10 is equal to or greater than 175 (in the observations, the number is 231), and 2) the interannual standard deviation of the Niño-3.4 index exceeds 0.9 (in the observations, the value is 1.16). The models that meet both criteria are classified into group A (CNRM-CM5, FGOALS-s2, GFDL CM3, MIROC5, MPI-ESM-LR, and NorESM1-M) and the remaining models are classified into group B.

Figure 11 shows the variances of low-level wind explained by the Niño-3.4 index over East Asia and surrounding areas in observations, and MME of groups A and B. The variances of U850 and V850 explained by ENSO are mainly observed over the northern part of the South China Sea in observations (Figs. 11a,d). This indicates that ENSO’s influences on the EAWM are mainly confined to the south of 30°N. In the extratropical regions, the climate variability is more influenced by atmospheric internal processes that are hard to predict by numerical models (Jiang et al. 2013). The MME in group A reproduced reasonable ENSO-related variances of U850 and V850 over East Asia (Figs. 11b,e), while the MME in group B captured a weaker ENSO-related U850 variance and failed to capture the ENSO-related variance of V850 over East Asia (Figs. 11c,f).

Figure 12 further shows the winter mean 850-hPa temperature and wind vector anomalies regressed onto the simultaneous normalized Niño-3.4 index in observations, and MME in groups A and B. The MME in group A captures the anticyclonic wind anomalies and positive temperature anomalies over the northwestern Pacific quite well although the simulated values of 850 hPa are somewhat weaker over the Indian Ocean than those in the observations (Fig. 12b). In contrast, the MME in group B cannot reproduce these features, with the simulated southeasterly and temperature anomalies being much weaker than in the observations (Fig. 12c). These results suggest that the atmospheric responses to ENSO over the western North Pacific and East Asia highly depend on the performance of ENSO-related SST features in models such as the spatial pattern and the strength of interannual variability. It further confirms our hypothesis that the representation of the ENSO–EAWM relationship in these CMIP5 models mainly depends on the simulation of ENSO.

4. Summary and discussion

Based on 30-yr output data from the historical run of 18 CMIP5 CGCMs, the ERA-40 reanalysis data, GPCP rainfall data, and ERSST (v3) data, this study presents a systematic evaluation of the climatology and the interannual variability of EAWM and the ENSO–EAWM relationship in these CMIP5 models. In the climatological mean sense, the CMIP5 models can successfully reproduce the geographical distribution and intensity of the major members of the EAWM system, including the Siberian high, Aleutian low, 500-hPa East Asian trough, 200-hPa East Asian jet streams, and 850-hPa wind and SAT over East Asia. The performances in SLP, SAT, Z500, and U200 are better than those of precipitation and V850 over East Asia in both spatial pattern and spatial standard deviation. Although a cold bias can still be observed in CMIP5 models over East Asia, the bias has been reduced much compared with that in CMIP3 models.

Based on an evaluation of six EAWM-related parameters, it is revealed that the MME can reproduce the intensity of the Siberian high and the Aleutian low very well. The intermodel spreads in SLP are large over the North Pacific and to the north of the Tibetan Plateau. This in turn leads to large intermodel spreads in both V850 and SAT over East Asia. Most of the models overestimate the magnitude of 850-hPa wind speed and Z500 over East Asia in boreal winter. This result is
consistent with Boo et al. (2011), who evaluated the AMIP data for the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4). This suggests that there are not significant improvements of CMIP5 models in these aspects. Besides the AMIP-type and CMIP-type runs, the negative Z500 bias over East Asia can also be found in hindcast of the National Centers for Environmental Prediction (NCEP) Climate Forecast System, version 2 (CFSv2), simulations (Jiang et al. 2013). Their results, in contrast, reveal positive SAT bias along the East Asian coast despite the negative Z500 bias. The reason for these differences is not clear and this deserves further investigation in the future.

The interannual standard deviations of several key variables related to the EAWM are evaluated to delineate the variability of the EAWM in models. The results suggest that the MME can generally reproduce reasonable EAWM-related variability in almost all the variables. More than half the models used in this study can capture the major features of the EAWM-related systems regarding the interannual variability. Three models (GISS-E2-H, GISS-E2-R, and INM-CM4) reveal weaker interannual variability than in the observations for all EAWM-related climate fields. The simulated amplitudes of interannual variability are almost identical to those in the observations for the Siberian high, the Aleutian low, and the 850-hPa wind speed over East Asia. The simulated climate anomalies represented by an EAWM index (Li and Yang 2010) in CMIP5 models are also examined. It turns out that the MME reproduces the EAWM index-related anomalies, including SAT, SLP, Z500, and U200 quite well although the simulated anomalies are slightly weaker over East Asia and the North Pacific. However, the MME fails to capture the EAWM-related northeasterly anomalies to the south of 30°N. Most models except for three (CNRM-CM5, GFDL CM3, and MIROC5) cannot reproduce the northeasterly anomalies in subtropical East Asia. This general bias may be accounted for by both the inadequacy of the EAWM index and the difficulty of reproducing the EAWM-related tropical–extratropical interactions in models.

To provide an intuitive understanding of the capacity of CMIP5 models in simulating the EAWM, a brief summary of the performance of individual models in
Simulating the EAWM is presented in Fig. 13. Here, the skill score was calculated to measure the ability of CMIP5 models in simulating the spatial patterns of climatology and interannual variability of the EAWM. The skill score for a spatial pattern (Taylor 2001) is defined as follows:

$$S = \frac{4(1 + R)^4}{(\hat{\sigma}_f + 1/\hat{\sigma}_f)^4(1 + R_0)^4},$$

where $R$ is the field correlation between the observed pattern and each model pattern, $R_0$ is the maximum correlation attainable (in this case, $R_0 = 1$), and $\hat{\sigma}_f$ is the ratio of the model’s pattern standard deviation against the observed pattern standard deviation. The skill takes both spatial correlation and amplitude into account to produce a quantitative measure of how each model simulation resembles the observational spatial pattern, including climatology and interannual variability spatial pattern. In general, almost all models show a tendency of high skill scores in simulating the climatological mean field (Fig. 13), especially for SAT, U200, and Z500. Compared with the simulations of climatological mean field, the skill scores of interannual variability patterns.
are much lower except for Z500 in most of models. In addition to Z500, SLP is the second best circulation field reproduced by most of models although its climatology is not as good as that of U200. The results suggest that Z500 and SLP in CMIP5 models are most reliable over East Asian region regarding both the climatology and the interannual variability. This is consistent with the previous conclusion in section 3b. Overall, the CNRM-CM5 model is the best model that reasonably captures all the EAWM-related circulation fields regarding both the climatology and the interannual variability. On the other hand, it is surprising that the skill scores of Pr are very high in both the climatology and the interannual variability fields, which are in sharp contrast to the summer situation. The high skill scores of Pr may be explained by the dry condition and small magnitudes of interannual variability of Pr over East Asia during boreal winter (see Fig. 6).

ENSO can exert important influences on the interannual variations of the EAWM, so the ENSO–EAWM relationship is examined in the CMIP5 models. Ten out of 18 models are able to reproduce the significant relationship between the EAWM and the Niño-3.4 indices. The maximum correlation coefficient is 0.74 in models, which is quite similar to that in the observations (−0.71). The possible factors that influence the simulated ENSO–EAWM relationship are discussed. It is very likely that a good spatial structure of ENSO-related SST anomalies and a reasonable strength of SST variability in the tropical central and eastern Pacific are

![Diagram indicating the relative ability of (top to bottom) the CMIP5 models in simulating from left to right the climatology (Clm) and interannual variability (Std) of EAWM based on 27 winters (1979–2005) for precipitation and based on 30 winters (1971–2000) for the remaining variables. The results are evaluated in the East Asian domain (20°–50°N, 100°–145°E). Label bar indicates the values of the skill scores for the spatial patterns.](image)
two key factors. Most of models that reveal strong (weak) ENSO–EAWM relationship are characterized by good (poor) spatial structure of ENSO-related SST anomalies and reasonable (weak) standard deviation of ENSO index. This implies that the capability of CMIP5 models in simulating ENSO can determine the ENSO–EAWM relationship to a large extent. This hypothesis is confirmed by dividing the CMIP5 models into two groups based on the spatial pattern of ENSO-related SST and the interannual variability of the Niño-3.4 index. The models that reasonably reproduce the spatial structure of ENSO-related SST and the interannual variability of ENSO (group A) can both capture the large variance of lower-tropospheric wind explained by ENSO and reproduce a reasonable anomalous anticyclone over the western North Pacific. In contrast, the rest of the models (group B) failed to capture the above two features.

The present analysis confirms previous studies that the anomalous anticyclone over the Philippine Sea is important to extend the influence of ENSO to the EAWM. This also provides a possible explanation of the bias of anticyclonic circulations over the western North Pacific in warm years by NCEP CFSv2 simulations (Jiang et al. 2013). On the other hand, it should be noted that the CSIRO Mk3.6.0 model reveals a good relationship between Niño-3.4 index and EAWM index \( r = -0.54 \) although it fails to capture the spatial structure of SST anomalies and interannual variability of ENSO. The cause of this phenomenon is unclear and needs further detailed analysis.

Previous studies suggest that the ENSO–EAWM relationship is not stationary and can change on decadal time scales (e.g., Zhou et al. 2007; Wang et al. 2008). Our preliminary analysis indicates that this changing ENSO–EAWM relationship can hardly be reproduced in CMIP models. One possible major reason is that the models cannot capture the Pacific decadal oscillation (PDO; Mantua et al. 1997). On the other hand, it is noteworthy that the interannual variability of the EAWM is associated not only with tropical factors such as ENSO but also with mid- and high-latitude factors such as Arctic sea ice, Eurasian snow cover, atmospheric blocking, and atmospheric teleconnection patterns (e.g., Wu and Wang 2002; Chen et al. 2005; Li and Yang 2010; B. Wang et al. 2010; L. Wang et al. 2010; Sohn et al. 2011; Cheung et al. 2012; Wei and Bao 2012; Wang and Chen 2014). The relationships between these extratropical factors and the EAWM in CMIP5 models are not discussed in this paper; this work is worthy of investigation in the future.

Acknowledgments. We thank the three anonymous reviewers for their valuable comments and suggestions that led to significant improvement of the manuscript.

We acknowledge the climate modeling groups (listed in Table 1) for producing and making available their model output. For CMIP the U.S. Department of Energy’s Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. This work was supported by the National Basic Research Program of China (2010CB428603), the National Natural Science Foundation of China (41230527, 41025017, and 41228006), the Jiangsu Collaborative Innovation Center for Climate Change, and the Chinese Academy of Sciences (KZCX2-EW-QN204).

REFERENCES


——, J. Feng, and R. Wu, 2013: Roles of ENSO and PDO in the link of the East Asian winter monsoon to the following summer monsoon. J. Climate, 26, 622–635.


