LETTER

Skillful seasonal predictions of winter precipitation over southern China

Bo Lu1,2,5, Adam A Scaife3, Nick Dunstone3, Doug Smith3, Hong-Li Ren1,2,4, Ying Liu1,2 and Rosie Eade3

1 Laboratory for Climate Studies, China Meteorological Administration, Beijing, 100081, People’s Republic of China
2 CMA-NJU Joint Laboratory for Climate Prediction Studies, Institute for Climate and Global Change Research, School of Atmospheric Sciences, Nanjing University, Nanjing, People’s Republic of China
3 Met Office Hadley Center, Exeter, United Kingdom
4 Department of Atmospheric Science, School of Environmental Studies, China University of Geoscience, Wuhan, 430074, People’s Republic of China
5 Author to whom any correspondence should be addressed.
E-mail: bolu@cma.gov.cn

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Abstract
Southern China experiences large year-to-year variability in the amount of winter precipitation, which can result in severe social and economic impacts. In this study, we demonstrate prediction skill of southern China winter precipitation by three operational seasonal prediction models: the operational Global seasonal forecasting system version 5 (GloSea5), the NCEP Climate Forecast System (CFSv2) and the Beijing Climate Center Climate System Model (BCC-CSM1.1m). The correlation scores reach 0.76 and 0.67 in GloSea5 and CFSv2, respectively; and the amplitude of the ensemble mean forecast signal is comparable to the observed variations. The skilful predictions in GloSea5 and CFSv2 mainly benefit from the successful representation of the observed ENSO teleconnection. El Niño weakens the Walker circulation and leads to the strengthening of the subtropical high over the northwestern Pacific. The anti-cyclone then induces anomalous northward flow over the South China Sea and brings water vapor to southern China, resulting in more precipitation. This teleconnection pattern is too weak in BCC-CSM1.1m, which explains its low skill (0.13). Whereas the most skilful forecast system is also able to simulate the influence of the Indian Ocean on southern China precipitation via changes in southwesterly winds over the Bay of Bengal. Finally, we examine the real-time forecast for 2015/16 winter when a strong El Niño event led to the highest rainfall over southern China in recent decades. We find that the GloSea5 system gave good advice as it produced the third wettest southern China in the hindcast, but underestimated the observed amplitude. This is likely due to the underestimation of the Siberian High strength in 2015/2016 winter, which has driven strong convergence over southern China. We conclude that some current seasonal forecast systems can give useful warning of impending extremes. However, there is still need for further model improvement to fully represent the complex dynamics of the region.

1. Introduction

China is located in the East Asian Monsoon region. Driven by the thermal contrast between the East Asian continent and surrounding oceans, the reversal of monsoonal flow is distinct which gives rise to a wet summer and dry winter climate over China. Numerous studies have focused on the summer rainfall variability (e.g. reviewed by Ding and Chan 2005). However, less attention is paid to the winter precipitation due to reduced climatological precipitation in winter; from December to January, the total accumulated precipitation is less than 50 mm over most part of China compared to 300 mm rainfall.
during the summer months. However, in southern China, the winter precipitation is higher than 100 mm accounting for about 15% of annual total rainfall (Li and Ma 2012). The standard deviation of accumulated southern China winter precipitation (SCWP) is large and can reach 50–120 mm, indicating remarkable interannual variability (figure 1). For example in January 2008, severe freezing rain and heavy snowfall occurred in South China, resulting in severe impacts on agriculture, electricity supply and transport (Ding et al 2008, Wang et al 2008). During the winter of 2009, a severe drought struck many parts of China, and SCWP was much lower than normal (Tao et al 2009). Given the distinct climatic, social and economic impacts, more studies of the variability and predictability of SCWP are needed.

Previous studies (Tao and Zhang 1998, Wu et al 2003) have shown that the variability of SCWP is modulated by the El Niño/Southern Oscillation (ENSO). During El Niño years, an anomalous anticyclone develops over the western North Pacific. The anomalous lower-level southwesterly winds to its northwest flank transport more water vapor from the ocean and favor more winter precipitation in southern China (Wang et al 2000, Zhang and Sumi 2002, Zhou et al 2010). However, this relationship between ENSO and SCWP is variable, with a stronger correlation after 1990s and a weaker correlation during the 1970s and 1980s (Li and Ma 2012). Therefore, other factors may also influence SCWP.

The sea surface temperature (SST) anomaly over the South China Sea (SCS) is another potential modulator of SCWP. Higher SST in SCS will generate southwesterly anomalies at 700 hPa, bringing more moisture and increased rainfall (Zhou et al 2010). SCWP is also found to be closely correlated with the eastern Indian Ocean SST (Peng 2012). When the eastern Indian Ocean is warmer than usual, local convection deepens the India–Burma trough, transporting more water vapor from the Bay of Bengal and intensifying SCWP. Apart from tropical SSTs, mid-latitude atmospheric circulation also affects SCWP. Zhou (2011) pointed out the impact of East Asian winter monsoon (EAWM) on SCWP. During weak

![Figure 1](image-url)

**Figure 1.** The climatology (a) and the standard deviation (b) of the winter total precipitation (mm). The white dashed boxes indicate the domain (110°E–123°E; 22°N–30°N) of southern China used in this study. (c) Seasonal predictions of the winter rainfall anomaly over the southern China. The observations and the hindcasts from GloSea5, CFSv2 and BCC-CSM1.1m are indicated by the black, red, green and blue curves, respectively. The red and blue dots represent the real-time seasonal predictions for 2015/2016 winter by GloSea5 and CFSv2, respectively. Note that year refers to January such that the winter indicated by 2016 on the x-axis indicates the 2015/2016 winter. The numbers in the parentheses represent the correlation coefficients between the observations and predictions over the common period of 1993–2010.
EAWM years, the East Asian westerly jet weakens and shifts southward, contributing to the increased ascent over southern China. A wet southern China is also accompanied by a weaker East Asian trough and a stronger Middle East jet stream (Zhang et al 2009).

Yang et al (2014) evaluated the SCWP prediction skill in five coupled models. Skillful predictions result from the reasonable representation of tropical SST and the associated atmospheric response. New generations of state-of-the-art models have since been developed. For example, the operational Global seasonal forecasting system version 5 (GloSea5) is better able to predict summer rainfall over the Yangtze River valley (Li et al 2016). Since the SCWP has increased markedly since the 1950s (Wang et al 2011, Lu and Ren 2016), it is now urgent that we investigate the prediction skill of SCWP in current operational models. By analyzing the hindcast results of GloSea5, the second version of the NCEP Climate Forecast System (CFSv2) and the version 1.1m of the Beijing Climate Center Climate System Model (BCC-CSM1.1m), this study evaluates the prediction skill and potential predictability of SCWP and investigates the key factors that influence prediction skill of these three operational models.

The remainder of the paper is organized as follows. Section 2 describes the observational and hindcasts datasets used in the study. In section 3, we examine the prediction skill and potential predictability of SCWP. The sources of predictability are discussed in section 4. And finally, a summary of the results is given in section 5.

2. Observational and hindcast datasets

Monthly precipitation over land and ocean are obtained from the CPC Merged Analysis of Precipitation (CMAP; Xie and Arkin 1997) covering the period since 1979. Observed atmospheric circulation is obtained from the National Centers for Environmental Prediction/Department of Energy (NCEP/DOE) Reanalysis 2 (Kanamitsu et al 2002), and SST observations are taken from HadISST (Rayner et al 2003).

GloSea5 is the operational seasonal forecasting system in MetOffice (MacLachlan et al 2015). The coupled HadGEM3 model is used in GloSea5. The atmosphere component uses MetUM (Met Office Unified Model; Brown et al 2012) atmosphere, and the ocean component uses NEMO (Nucleus for European Modelling of the Ocean; Madec 2008). GloSea5 uses the N216 version (0.8° in latitude and 0.5° in longitude) for the atmosphere, and the ORCA0.25 grid (0.25°) for the ocean. There are 85 vertical levels for the atmosphere and 75 levels for the ocean. The model contains no flux corrections or relaxations to climatology. The GloSea5 Ocean and Sea Ice Analysis (1989–2011) supplies initial conditions for the ocean and sea ice, and ERA-Interim reanalysis data is used to initialize the atmosphere and land surface in the hindcast members. GloSea5 hindcast experiments used in this study were performed for winter prediction (December to February), initialized on 25 October, 1 November and 9 November from 1992 to 2011. Each start date has eight ensemble members with different stochastic parameterization of model physics (Tennant et al 2011), thus totaling 24 ensemble members per winter.

In March 2011, CFSv2 was made operational at NCEP (Saha et al 2014). CFSv2 is a fully coupled model representing the interaction between the Earth’s atmosphere, oceans, land and sea ice. A coupled atmosphere–ocean–sea ice–land reanalysis for 1979–2010 (CFSR) is used to create initial conditions for CFSv2 retrospective forecasts. The 9 month hindcasts have initial conditions of the 0000, 0600, 1200 and 1800 UTC cycles for every 5th day over the period 1982–2009. In this study, we analyze the prediction initialized in November (8 Oct, 13 Oct, 18 Oct, 23 Oct, 28 Oct, 2 Nov and 7 Nov) with 28 members each year.

The current operational model for seasonal prediction in Beijing Climate Center is BCC-CSM1.1m (Wu et al 2010). Its ocean component is developed by modifying MOM4 from Geophysical Fluid Dynamics Laboratory (Griffies et al 2004). Its horizontal resolution is 1°×1° poleward of 30°N and 30°S, incrementally increasing to 1/3° latitude within 30°N and 30°S. This ocean model has 40 vertical layers and includes dynamic and thermodynamic Sea Ice Simulator (SIS; Winton 2000). The atmospheric component is the BCC_AGCM2.2 at T106 horizontal resolution and 26 vertical layers (Wu et al 2008), and the land model is BCC_AVIM (Ji et al 2008) with a same horizontal resolution as the atmospheric model. BCC–Godas ocean reanalysis is used to initialize the ocean (Liu et al 2005), while initial atmosphere and sea ice conditions are nudged toward NCEP reanalysis (Kanamitsu et al 2002) and NOAA Optimum Interpolation Ice Concentration data (Reynolds et al 2002), respectively. The hindcast experiments were performed at the beginning of every month from 1991 to 2014, with 24 members per prediction by lagged initial dates (15 members) and singular vector perturbation method (9 members; Kleeman et al 2003). In this study, we only consider the predictions for the boreal winter, initialized in every November.

3. Predictability of the winter precipitation over southern China

The seasonal predictions for SCWP in GloSea5, CFSv2 and BCC-CSM1.1m are shown in figure 1. The correlation coefficient is as high as 0.76 between GloSea5 and the observed precipitation (statistically significant at the 99% confidence level using a student-t test) over the common period of all the models from
1993 to 2010. CFSv2 is also capable to predict the interannual variation of SCWP, with significant correlation skill reaching 0.67. However, the prediction skill is low (0.13) in BCC-CSM1.1m and not statistically significant. The cross-validation analysis is performed when doing the bias correction in models, and the ACC skill remains almost unchanged. We also analyzed the land only precipitation over southern China using GPCC observations (Schneider et al. 2014), and the results are consistent (not shown).

Another interesting feature is the amplitude of SCWP. Unlike the ensemble mean prediction of North Atlantic Oscillation (NAO) by GloSea5 (Scaife et al. 2014), the SCWP amplitude in GloSea5 ensemble mean predictions is similar to the observed variations. The standard deviations of the predicted SCWP are 41 mm and 35 mm by GloSea5 and CFSv2, respectively, which are comparable to the observed value of 61 mm. The signal in BCC-CSM1.1m ensemble prediction is small (14% of the observed amplitude), with mainly uncorrelated ‘noise’ between different members. For the extreme wet winters in 1994/1995 and 1997/1998, SCWP in the GloSea5 hindcast is very close to the observations. Both GloSea5 and CFSv2 are able to predict the dry winter in 1998/1999. However, the driest winter in 2008/2009 is missed by all three models. The observed rainfall anomaly is −108 mm, while only two ensemble members in GloSea5 predicted the observed amplitude. This result is consistent with the previous finding that dry winters are more difficult to predict (Yang et al. 2014).

We further examine the spatial patterns of the winter precipitation prediction skill over the Indo-Pacific region within the common period among three models. As shown in figure 2, the skill for all three models is the highest in the equatorial central to eastern Pacific with temporal correlations exceeding 0.8, which is consistent with previous studies (Peng et al 2011, Kim et al 2012, Kumar 2014, Scaife et al 2017). Since winter rainfall over China is modulated by convection over the tropical Pacific (Li and Ma 2012), this good prediction skill is consistent with skilful predictions of SCWP. As suggested by Peng (2012), convection over the eastern Indian Ocean can also affect SCWP. Thus, we also assess the predictability of winter rainfall over the Indian Ocean. The western basin is well predicted by all three models. However, only GloSea5 is able to predict the winter rainfall over the eastern Indian Ocean and the Bay of Bengal. Winter rainfall over the western Pacific is predicted very well by all the models, but the skill over the northern South China Sea is low. For southern China, high prediction skill is observed in GloSea5 and CFSv2, and the predictable region extends eastward to the Eastern China Sea. The skill over southern China is low in BCC-CSM1.1m, and no significant correlation is observed. This skill pattern is also confirmed by using the station dataset over China (not shown).

Since the common period (1993–2010) is relatively short among three models, we further check the skill patterns over the whole hindcast period in GloSea5 (1993–2012), CFSv2 (1983–2010) and BCC-CSM1.1m (1992–2015), and the results are consistent (supplementary figure 1 available at stacks.iop.org/ERL/12/074021/mmedia).

Recent studies have shown that seasonal prediction skill depends on ensemble size. For example, the seasonal prediction skills of summer Yangtze river
rainfall (Li et al 2016) and NAO (Scaife et al 2014) both increase with a larger ensemble size. Here we estimate the importance of ensemble size for SCWP predictions in GloSea5 and CFSv2. Note that the members in different years are independent. For example, the 18th member in 2005 is independent with the 18th member in 2004. Thus, large samples can be generated by randomly combining various ensembles in different years. In this study, 10000 samples are generated for each ensemble size for computational effectiveness. As shown in figure 3(b), the skill for a single member prediction is only 0.49 in GloSea5, but the skill increases to 0.76 for the ensemble mean of 24 members (thick black curve). The prediction skill in CFSv2 also increases from 0.39 with single member to 0.67 with the ensemble mean of 28 members (figure 3(d)). It is also found that at least 10 members are needed to capture most of the SCWP prediction skill, and the skill then remains stable when even larger members are included. This skill changes with various member sizes follow the theoretical relationship suggested by Murphy (1990) very well in both models (red dots), which is consistent with previous studies of NAO predictions (Scaife et al 2014, Dunstone et al 2016) and China summer rainfall predictions (Li et al 2016). The theoretical skill limit for a very large ensemble size is 0.78 (0.69) in GloSea5 (CFSv2), close to that of the current ensemble prediction systems. We have also assessed the effect of member size in BCC-CSM1.1m (supplement figure 2). The prediction skill increases with ensemble size, however, its theoretical limit is only 0.26 which is still not significant. This implies that rather than more ensemble members, better physical representation of the key processes is needed for BCC-CSM1.1m to produce skilful SCWP prediction. The potential predictability is also estimated based on the "perfect model" assumption that the observation can be replaced by an arbitrary ensemble member. Interestingly, the potential predictability is lower than the prediction skill (green curve in figures 3(b) and (d)). A similar effect occurs with the NAO predictions by AGCM (Mehta et al 2000) and GloSea5 (Scaife et al 2014, Dunstone et al 2016), implying that it is easier to predict the real SCWP than another ensemble member in GloSea5 and CFSv2. The discrepancy between the observations and individual model members can be quantified by the ratio of predictable components (RPC; Eade et al 2014). For SCWP prediction by GloSea5 and CFSv2, similar RPCs = 1.2 are obtained, indicating that the predictable component of the observed SCWP is slightly larger than that in the
model. It should also be noted that this RPC = 1.2 is close to the ideal value of 1, and the SCWP amplitude is comparable to the observations when multi-member mean is applied (figures 3(a) and (c)). The total ensemble spreads are 0.71 and 0.66 mm day\(^{-1}\) in GloSea5 and CFSv2, respectively, which agrees well with the observed interannual variability of 0.7 mm day\(^{-1}\). However, our results suggest higher skill is possible in future if the slight weak signal to noise ratio can be overcome with improved models.

4. Sources of prediction skill

We now investigate the physical processes that give rise to skilful SCWP predictions. Figure 4 shows the anomalies of SST and horizontal wind at 850 hPa regressed onto SCWP over the common period of three models. As an effort to increase the sample size in three models, single members, rather than the ensemble mean, are utilized during the regression. Over the tropical Pacific, an El Niño like SST pattern is evident in the observations, consistent with previous studies finding that warming over eastern Pacific often favors a wetter winter over southern China (Li and Ma 2012). This El Niño like SST pattern is well reproduced by GloSea5 and CFSv2, however, this signal is missed in BCC-CSM1.1m. Since the skilful seasonal predictability of the winter rainfall often comes from the tropical Pacific (Yang et al 2014), the resultant prediction skill for SCWP is lower than the other two models (figure 1). The spatial correlations of the regressed SST pattern against the observations are 0.92, 0.86 and 0.16 for GloSea5, CFSv2 and BCC-CSM1.1m, respectively. The results for the whole period of the hindcast by three models are shown in supplementary figure 3, which is consistent with that for the common period. As an effort to improve the seasonal prediction skill, we further investigate the reason why SCWP is uncorrelated with ENSO in BCC-CSM1.1m. In fact, the seasonal prediction of ENSO itself is very good by BCC-CSM1.1m. Ren et al (2017) showed that the ACC skill of Niño3.4 anomaly remains higher than 0.75 even 6 months ahead. Thus, the error in BCC-CSM1.1m may come from the ENSO teleconnection. Figure 5 shows the regression patterns of the winter precipitation and the horizontal wind at 850 hPa against Niño3.4 anomaly. In the observations, the westerly wind is pronounced over the equatorial Pacific, indicating the slowdown of Walker circulation. The subsidence over the maritime continent induces the anomalous anti-cyclone over the northwestern Pacific. Therefore, the ENSO-induced SCWP is insignificant, which explains the reason for the low skill of BCC-CSM1.1m and sheds some light on required model improvement. The analysis over the whole hindcast period of three models gives a consistent result (supplementary figure 4). We also randomly pick prediction members in three models with different ENSO teleconnections. The results confirm that stronger ENSO-teleconnection is weak over the northwestern Pacific. Therefore, the ENSO-induced SCWP is insignificant, which explains the reason for the low skill of BCC-CSM1.1m and sheds some light on required model improvement. The analysis over the whole hindcast period of three models gives a consistent result (supplementary figure 4). We also randomly pick prediction members in three models with different ENSO teleconnections. The results confirm that stronger ENSO-teleconnection is weak over the northwestern Pacific.
physical processes than ENSO for SCWP prediction, especially during non-ENSO years. Previous studies suggested that the tropical Indian Ocean can also affect the winter precipitation in southern China (Peng 2012). The convection over the eastern Indian Ocean can modulate the variability of India–Burma trough which controls the moisture transport from the Bay of Bengal to south China. The rainfall over eastern Indian Ocean and the Bay of Bengal is well predicted by GloSea5, with significant correlation coefficient exceeding 0.5 (figure 2(a)). However, CFSv2 and BCC-CSM1.1m fail to predict rainfall there. The correlation skill is even negative over the Bay of Bengal in both models (figures 2(b) and (c)). This low prediction skill results from the overestimation of the local air-sea interaction over the eastern Indian Ocean and the Bay of Bengal. It is well known that the Indian Ocean warms up following El Niño events (Weare 1979), which is reproduced by all three models (not shown). Changes in cloud cover and evaporation during El Niño increase the heat flux and hence the SST over the Indian Ocean (Klein et al 1999). Indian Ocean warming is a result of the ENSO-induced subsidence over the eastern basin. Thus, precipitation is below normal in the observations and GloSea5 (figures 5(a) and (b)), despite the underlying warm ocean. However, CFSv2 and BCC-CSM1.1m fail to predict rainfall there. The correlation skill is even negative over the Bay of Bengal in both models (figures 2(b) and (c)). This low prediction skill results from the overestimation of the local air-sea interaction over the eastern Indian Ocean and the Bay of Bengal. It is well known that the Indian Ocean warms up following El Niño events (Weare 1979), which is reproduced by all three models (not shown). Changes in cloud cover and evaporation during El Niño increase the heat flux and hence the SST over the Indian Ocean (Klein et al 1999). Indian Ocean warming is a result of the ENSO-induced subsidence over the eastern basin. Thus, precipitation is below normal in the observations and GloSea5 (figures 5(a) and (b)), despite the underlying warm ocean. However, the ENSO-induced Walker circulation changes are too weak within the Indian Ocean basin, and the subsidence occurs in the northwestern Pacific only in CFSv2 and BCC-CSM1.1m (figures 5(c) and (d)). Following the heating from the warm ocean, the increased rainfall is evident over the eastern Indian ocean, which is unrealistic. As shown in figure 4(a), the observed SCWP is affected by both the moisture from SCS and the Bay of Bengal. This feature is well captured by GloSea5. However, due to the low skill in predicting the convection over the Bay of Bengal, the southwesterly wind in the front of India–Burma trough is not simulated by CFSv2, potentially explaining why GloSea5 outperforms CFSv2 in SCWP prediction.

Other than the impact from the tropical ocean, the strength of EAWM can also modulate winter rainfall over southern China. Weak EAWM often favors stronger SCWP by the southward movement of the East Asian westerly jet (Zhou 2011). The EAWM is largely controlled by the circulation anomalies in the middle and high latitudes, such as the Siberian high (Gong et al 2001), which is difficult to predict one season ahead. Thus, the EAWM was previously considered as ‘noise’ in SCWP predictions (Yang et al 2014). The predictability of EAWM has been evaluated using DEEMETER (Li and Wang 2012) and ENSEMBLES (Yang and Lu 2014) datasets. Previous results suggest that predictability of EAWM depends on the index definition. The EAWM indices with high prediction skill originate from their high relationship with ENSO (Yang and Lu 2014). In order to focus on the predictive signal from middle to high latitude, we evaluate the EAWM index defined by Wang and Chen (2014). This index is calculated based on sea level pressure from various regions including Siberian high, which is unpredictable with the skill from 0.1 to 0.25 by ENSEMBLES (Yang and Lu 2014). As shown in table 1, the prediction skills of this EAWM index are...
0.46 and 0.40 in BCC-CSM1.1m and CFSv2, respectively, which are both statistically significant at 95% confidence level. The skill for GloSea5 prediction is 0.35, which is lower but still significant at 90% confidence level. The skillful prediction of EAWM therefore offers extra skill in SCWP prediction other than ENSO. The Middle East jet stream is another atmospheric factor affecting SCWP (Zhang et al 2009). However, the prediction skill of MEJS is low in all three models (table 1).

5. Summary and discussion

This study investigates the seasonal prediction skill of winter rainfall over southern China by three current operational models (GloSea5, CFSv2 and BCC-CSM1.1m). Skilful predictions are evident in GloSea5 and CFSv2, with the temporal correlation reaching 0.75 and 0.67, respectively. The principal source of predictability is ENSO, induces an anticyclonic anomaly over northwestern Pacific, which brings moisture from the SCS and intensifies the winter rainfall over southern China. This typical ENSO teleconnection pattern is well captured by GloSea5 and CFSv2, giving rise to the high prediction skill in these models. However, the ENSO-induced anticyclone is too weak in BCC-CSM1.1m. Hence, SCWP is uncorrelated with ENSO in BCC-CSM1.1m, explaining the relative low skill in BCC-CSM1.1m. Lu and Ren (2016) found out that the weak ENSO teleconnection in BCC-CSM1.1m is due to the deficiency of the cumulus representation. By enhancing the entrainment rate, a stronger ENSO-induced convection is observed and the resultant atmospheric response is more realistic. This result would shed some light on the model development in BCC. Although the current SCWP prediction is low in BCC-CSM1.1m, skilful prediction can be achieved by statistical downscaling. Using the predicted winter Niño3.4 index by BCC-CSM1.1m and the observed ENSO-SCWP relationship, the prediction skill reaches 0.7. This skilful downscaling prediction works only when the ENSO-SCWP relation is strong. However, this correlation is weak during the 1970s and 1980s (Li and Ma 2012), which may explain the lower prediction skill by CFSv2 when including the hindcast period in 1980s (supplementary figure 1(b)) compared with the skill during the overlap hindcast period in 1990s and 2000s (figure 2). This unstable correlation highlights the need for models to represent any sources of predictability other than ENSO.

The Indian Ocean is another prediction source for SCWP. The convection over the eastern Indian Ocean is able to modulate the strength of India–Burma trough and affect the water vapor transport from the Bay of Bengal to South China. The convection over the eastern Indian Ocean is well predicted by GloSea5. However, due to the eastward shift of ENSO-induced Walker circulation change, the rainfall prediction skill by CFSv2 is low over the eastern Indian Ocean and the Bay of Bengal. Thus, SCWP prediction skill by CFSv2 is slightly lower than that by GloSea5. The winter rainfall over southern China is also influenced by EAWM. We show that EAWM is moderately predictable by all three models, potentially providing some predictability for SCWP.

The above assessment is based on hindcast experiments. We also validate the real-time forecasts for 2015/2016 winter issued at the beginning of November 2015. The 2015/2016 winter is the wettest on record since the 1990s, with the observed SCWP anomaly reaching 183 mm. The SCWP predicted by GloSea5 is 42 mm, which is the third strongest rainfall in the GloSea5 predictions (red dot in figure 1(c)). Since a joint record El Niño occurred during the 2015/2016 winter, the anti-cyclone was enhanced over the northwestern Pacific (supplement figure 6). The resultant strengthening of southeasterly wind from the SCS was well captured by GloSea5, which brought moisture to south China. However, the enhanced anticyclone in BCC-CSM1.1m was too weak and shifted southeastward compared with observations. Thus, BCC-CSM1.1m predicted a normal winter for southern China (blue dot in figure 1(c)). In the observations, strong northerly wind was also evident over north China. This strengthening of the winter monsoon circulation is unusual during an El Niño year, because EAWM is often negatively correlated with ENSO (Li 1990). This unusual strong cold and dry northerly wind converged with the warm and wet wind in southern China, and resulted in extra heavy rainfall in 2015/2016 winter. However, this unusual strong EAWM was not predicted by GloSea5 or BCC-CSM1.1m.

It should be also noted that climate ‘disasters’ often occur on monthly rather than seasonal timescales. For example, the severe snow and freezing rainfall in 2007/2008 winter mainly happened in January, but is unclear for the December to February mean precipitation (black curve in figure 1(c)). Although the total winter precipitation can be well predicted by GloSea5 and CFSv2, further work is needed on the skill of predicting monthly extremes by dynamical or statistical methods (e.g. Wu et al 2011).

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