Seasonal–Interannual Variation and Prediction of Wet and Dry Season Rainfall over the Maritime Continent: Roles of ENSO and Monsoon Circulation

TUANTUAN ZHANG
Department of Atmospheric Sciences, Sun Yat-sen University, Guangzhou, Guangdong, China

SONG YANG
Department of Atmospheric Sciences, and Institute of Earth Climate and Environment System, Sun Yat-sen University, Guangzhou, Guangdong, China

XINGWEN JIANG
Institute of Plateau Meteorology, China Meteorological Administration, Chengdu, Sichuan, China

PING ZHAO
State Key Laboratory of Severe Weather, Chinese Academy of Meteorological Sciences, Beijing, China

(Manuscript received 24 March 2015, in final form 21 September 2015)

ABSTRACT

The authors analyze the seasonal–interannual variations of rainfall over the Maritime Continent (MC) and their relationships with El Niño–Southern Oscillation (ENSO) and large-scale monsoon circulation. They also investigate the predictability of MC rainfall using the hindcast of the U.S. National Centers for Environmental Prediction (NCEP) Climate Forecast System version 2 (CFSv2).

The seasonal evolution of MC rainfall is characterized by a wet season from December to March and a dry season from July to October. The increased (decreased) rainfall in the wet season is related to the peak-decaying phase of La Niña (El Niño), whereas the increased (decreased) rainfall in the dry season is related to the developing phase of La Niña (El Niño), with an apparent spatial incoherency of the SST–rainfall relationship in the wet season. For extremely wet cases of the wet season, local warm SST also contributes to the above-normal rainfall over the MC except for the western area of the MC due to the effect of the strong East Asian winter monsoon.

The CFSv2 shows high skill in predicting the main features of MC rainfall variations and their relationships with ENSO and anomalies of the large-scale monsoon circulation, especially for strong ENSO years. It predicts the rainfall and its related circulation patterns skillfully in advance by several months, especially for the dry season. The relatively lower skill of predicting MC rainfall for the wet season is partly due to the low prediction skill of rainfall over Sumatra, Malay, and Borneo (SMB), as well as the unrealistically predicted relationship between SMB rainfall and ENSO.

1. Introduction

The Maritime Continent (MC) consists of multiple islands of Southeast Asia including Sumatra, Java, Borneo, and New Guinea and oceanic areas of the equatorial western Pacific. It is a “land bridge” connecting the continental areas of East/Southeast Asia and Australia (e.g., Chang et al. 2005b; Lau and Chan 1983; Meehl 1987; Matsumoto 1992; Matsumoto and Murakami 2002; Yasunari 1991). The MC region lies within the Indo-Pacific warm pool, where evaporation from warm water increases atmospheric moisture, and atmospheric circulation transports abundant water vapor from the surrounding oceans toward the MC (Qian 2008). Consequently, the MC forms the largest rainy region on the earth (Qian 2008; Simpson et al. 1993).
The unique geographical location of MC and the complex distribution of land, sea, and terrains contribute to significant variations of rainfall over the region on various temporal and spatial scales. Chang et al. (2005b) indicated that the large annual cycle dominates the MC rainfall variability, but the rainfall also exhibits significant local features. Based on the relative amplitudes of annual and semiannual cycles of the rainfall and the occurrence months of maximum rainfall, Hamada et al. (2002) classified 46 Indonesian stations objectively into different types of rainfall variations and analyzed their different features. A prominent diurnal cycle was also demonstrated in the MC rainfall, mostly concentrated over islands in afternoons and evenings, with a secondary maximum over the seas between large islands during the late night and morning hours (e.g., Hara et al. 2009; Neale and Slingo 2003; Qian 2008; Yang and Slingo 2001).

The MC is also known as a “boiler box” (Ramage 1968). Large amounts of latent heat are released from the rainfall processes over MC and transported to other places through the Hadley cell and the Walker circulation. Previous studies have shown that the annual cycle of MC rainfall is modulated largely by the interaction between the complex terrain and a simple annual reversal of monsoon flow throughout regions from the Indian Ocean (IO) to the South China Sea (SCS) and the equatorial western Pacific (Chang et al. 2005b). It has also been reported that the northeasterly cold surge exerts an impact on the convection over MC (e.g., Chang and Lau 1982; Lau et al. 1983; Lau and Chang 1987; Chang et al. 2005a). Dayem et al. (2007) indicated that enhanced rainfall over MC led to an increased zonal pressure gradient but a decreased meridional gradient. The MC rainfall also exhibits significant interannual variations (Chang et al. 2004). Particularly, the Indonesian rainfall is highly correlated with El Niño–Southern Oscillation (ENSO) in dry and transition seasons but poorly related to ENSO in the wet season (e.g., McBride and Nicholls 1983; Haylock and McBride 2001; Hendon 2003). Chang et al. (2004) showed that the rainfall over the central MC was significantly correlated with ENSO and pointed out that low correlation would be obtained between the Indonesian monsoon rainfall and ENSO if the rainfall in the two regions (east and west of 112°E over Indonesia) with opposite characteristics were averaged. McBride et al. (2003) hypothesized that the interannual variation of MC rainfall was a direct response to the upstream boomerang pattern of sea surface temperature (SST), a basic component of ENSO.

The importance of MC for local and global atmospheric circulations has characterized the region as a fascinating place for many studies. However, prediction of the MC rainfall is always a huge challenge due to the complex system of islands and shallow seas. Most atmospheric general circulation models (GCMs) substantially underestimate the rainfall over the MC and there is little improvement even with an increase in model horizontal resolutions (Neale and Slingo 2003). Meanwhile, deficient rainfall over the MC could be a driver for other systematic errors (Yang and Slingo 2001; Neale and Slingo 2003). Jiang et al. (2013c) reported that improving the simulation of convection over MC potentially enhanced the skill of predicting the East Asian winter monsoon (EAWM).

Substantial effort has been devoted to investigating the seasonal forecast skill of numerical models (e.g., Jia and Lin 2013; Jia et al. 2012, 2014a,b) and the predictability of rainfall over MC. Based on the relationship between coherence and predictability, Haylock and McBride (2001) concluded that the wet season rainfall in Indonesia was inherently unpredictable. Experiments with a climate version of the Met Office model (HadAM3) suggested that significantly improving the diurnal cycle of MC rainfall could potentially reduce the model’s large-scale systematic errors (Neale and Slingo 2003). More recently, improvements have been found in a 20 km-grid Meteorological Research Institute General Circulation Model (MRI-GCM) in simulating MC rainfall (e.g., Arakawa and Kitoh 2005; Hara et al. 2009). However, deficiencies still exist, especially over the islands with horizontal scales larger than 200 km such as Sumatra and Borneo (Hara et al. 2009). Therefore, the predictability of MC rainfall needs further investigation. While most previous studies tended to assess simulation skills of GCMs, here we attempt to provide a comprehensive understanding of MC rainfall prediction and the dynamical and physical processes related to the variability and predictability of the regional rainfall based on dynamical seasonal prediction output from the NCEP Climate Forecast System (CFS).

The NCEP CFS is a state-of-the-art operational climate forecast system that provides operational prediction of the world’s climate including the rainfall over the Indo-Pacific regions (Saha et al. 2006). The first version of the CFS (CFSv1), which became operational in August 2004, showed reasonable skills in predicting the major features of large-scale climate such as ENSO (e.g., Wang et al. 2005) and the Asian monsoon (Yang et al. 2008a,b; Achuthavarier and Krishnamurty 2010; Drbohlav and Krishnamurthy 2010; Gao et al. 2011). The NCEP CFSv1 was replaced by the second version (CFSv2) in 2011 and the NCEP CFSv2 demonstrates improved skills in predicting global land rainfall, surface air temperature (Yuan et al. 2011), large-scale monsoon circulation (Jiang et al. 2013b), the climate anomalies related to IO basinwide warming (Jiang et al. 2013a),
and extratropical climate (Gao et al. 2014). The CFSv2 can also predict the rainfall patterns of the Indo-Pacific monsoon and North American monsoon by several months in advance, but it exhibits little predictive skill for the Africa monsoon rainfall (Zuo et al. 2013). Although assessment of the capability of CFSv2 in predicting rainfall and atmospheric circulation over a wide range of regions has been provided, the prediction skills for MC rainfall variations and their relationships with the large-scale climate anomalies remain unknown.

The rest of this paper is organized as follows. The CFSv2 hindcast and observational data are described in section 2. The variability of MC rainfall and its relationships with large-scale features are discussed in section 3. In sections 4 and 5, we investigate the prediction of MC rainfall and its relationships with large-scale climate

FIG. 1. Climatology (1983–2010) of observed rainfall (mm day⁻¹, shading) and 850-hPa winds (m s⁻¹, vectors) from January to December. The domain used to define the MC (15°S–10°N, 95°–145°E) is outlined with red boxes.
patterns. Finally, a summary of the study and further discussion are provided in section 7.

2. Model, data, and methods

The NCEP CFSv2 (Saha et al. 2010) consists of the NCEP Global Forecast System model with a T126 horizontal resolution and 64 sigma vertical layers, the Geophysical Fluid Dynamics Laboratory Modular Ocean Model version 4.0, the Noah four-layer land surface model, and a three-layer interactive global sea ice model. We analyze the monthly output of rainfall, 850-hPa winds, and SST from the retrospective forecasts of 9-month integrations by the CFSv2 from 1983 to 2010. The 9-month hindcast runs were initialized from every 5th day and run from 0000, 0600, 1200, and 1800 UTC of that day, forming a monthly 24-member ensemble. More details about the initial time can be found at http://cfs.ncep.noaa.gov/cfsv2.info/. For the 24-member runs for a specific starting month, say June, the initial conditions of 11, 16, 21, 26, and 31 May and 5 June are for 0-month lead, with initial dates after the 7th of the particular month used as the ensemble member for the next month.

The observations used for model verification include the Climate Prediction Center (CPC) Merged Analysis of Rainfall (CMAP; Xie and Arkin 1997) and the winds from the NCEP Climate Forecast System Reanalysis (CFSR; Saha et al. 2010). They also include SST from the National Oceanic and Atmospheric Administration optimally interpolated SST analysis (Reynolds et al. 2007).

![Fig. 2. Observed monthly mean of MC rainfall (mm day$^{-1}$, black line) and its standard deviations (shading) from January to December. The horizontal line denotes the annual average of MC rainfall.](image1)

![Fig. 3. Anomalies of observed rainfall (mm day$^{-1}$, shading) and 850-hPa winds (m s$^{-1}$, vectors) in the (a) wet season (December–March) and (b) dry season (July–October). The domain used to define the MC is outlined with red boxes.](image2)

![Fig. 4. Time series of observed MC rainfall (mm day$^{-1}$) for wet (line with open circles) and dry (line with pluses) seasons.](image3)
In this study, the Niño-3.4 index is defined by the SST averaged over the area of 5°S–5°N, 120°–170°W. The EAWM index (IEAWM) defined by Li and Yang (2010) is also used: $\text{IEAWM} = [(U1 - U2) + (U1 - U3)]/2$, where $U1$ is the 200-hPa zonal wind averaged over the area of 30°–35°N, 90°–160°E, $U2$ is averaged over the area of 50°–10°N, 70°–170°E, and $U3$ is averaged over the area of 5°S–10°N, 90°–160°E. A partial correlation analysis $R_{ab,c} = (R_{ab} - R_{ac}R_{bc})/\sqrt{(1 - R_{ac}R_{ac})(1 - R_{bc}R_{bc})}$ is applied to exclude the possible influence by ENSO (Sankar-Rao et al. 1996; Ashok et al. 2007). In the equation, $R_{ab,c}$ is the partial correlation coefficient between MC rainfall index $a$ and variable $b$ after the influence of ENSO is removed. The term $R_{ab}$ is the coefficient of correlation between MC rainfall index $a$ and variable $b$; similarly, $R_{ac}$ is between MC rainfall index $a$ and Niño-3.4 index $c$, and $R_{bc}$ between variable $b$ and Niño-3.4 index $c$. The Student’s $t$ test is used to assess the statistical significance of the results obtained.

3. Variations of MC rainfall and relationships with large-scale circulation patterns

a. Climatological features and interannual variations of MC rainfall

Figure 1 shows the climatologies of rainfall and 850-hPa winds from January to December, in which the domain used to define MC (15°S–10°N, 95°–145°E) is outlined with red boxes. The rainband is located over the MC region from November to April, and then jumps northward in May with the development of southerly winds over the northern IO and East Asia, southeasterly winds over the western Pacific, and cross-equatorial flows. The rainfall centers over the northern part of the MC may be ascribed to the interaction between terrains and the moist southerly monsoon flow (Chang et al. 2005b). Such a wind–terrain interaction can be clearly seen in June, with heavy rainfalls over the west of India, the Indo-China Peninsula, and the SCS. Heavy rainfall gradually returns to the MC.
around October, with establishment of high-latitude circulation systems such as the Siberian high and reversal of the cross-equatorial flow. It is also interesting to note that heavy rainfall is always observed in the west of Sumatra, even when other MC regions are dry. This feature may be partly due to a strong wind–terrain interaction (Chang et al. 2004), as well as to local diurnal circulation (Mori et al. 2004, 2011). Correspondingly, convergence is observed at 850 hPa over MC from November to April, whereas divergence is seen from June to September.

The above analysis indicates that the annual evolution of MC rainfall is clearly characterized by a wet season and a dry season. We define July–October as the dry season and December–March as the wet season according to the monthly evolution of rainfall over the MC (see Fig. 2). The wet season of a particular year refers to January–March of the current year and December of the previous year, except that the wet season of 1983 refers to January–March of 1983. Not only the rainfall amount but also the standard deviation of MC rainfall is larger in the wet season than in the dry season.

Figure 3 shows the anomalies that are relative to the annual mean values of observed rainfall and 850-hPa winds for wet and dry seasons. Clearly, in the wet season an anomalous cyclonic circulation is located over the tropics south of 10°N, which favors heavy rainfall over the MC. In the meantime, an anomalous anticyclonic circulation is located to the north of 10°N, which suppresses local rainfall (Fig. 3a). The patterns of rainfall and winds exhibit opposite-signed features in the dry season (Fig. 3b).

An index measuring the interannual variability of MC rainfall is defined as the average rainfall over the MC region outlined by the red boxes in Figs. 1 and 3 for wet and dry seasons, respectively. Figure 4 shows that, in the wet season, the MC rainfall reaches a maximum about 9.9 mm day$^{-1}$ in 1999 and a minimum below 5 mm day$^{-1}$ in 1983. It should be noted that the precipitation in December 1982 is not included in the wet season of 1983, which may have an effect on the wet season rainfall amount of 1983. In the dry season, the maximum rainfall is 7.4 mm day$^{-1}$ in 2010, and the minimum is 3.2 mm day$^{-1}$ in 1997. By definition, the rainfall
amount in wet season is generally larger than that in dry season for a particular year, but exceptions (the rainfall amount in dry season even larger than that in wet season) occurred in 1983, 1992, 1998, and 2010 due to the significantly deficient rainfall in the wet seasons of 1983, 1992, and 1998 and the excessive rainfall in the dry season of 2010. An analysis of rainfall, 850-hPa winds, and SST shows El Niño–like patterns for the wet season of exceptional years (e.g., the wet season in 1998) and La Niña–like patterns for the dry season of exceptional years (e.g., the dry season in 2010). The wet season MC rainfall is usually below normal in El Niño years, and the dry season MC rainfall is often above normal in La Niña years. The relationships between the extremely dry or wet events and ENSO will be discussed in the next section. In addition, the coefficient of correlation between the wet season rainfall and the following dry season rainfall is −0.07, but it is 0.64 (exceeding the 99% confidence level) between the rainfalls in the dry season and in the next wet season. This feature indicates that a dry season with excessive rainfall is usually followed by an exceptionally wet season, but an exceptionally wet season is not necessarily followed by a dry season with excessive rainfall, and vice versa.

b. Relationships between MC rainfall variations and large-scale climate anomalies

For the wet season, when the MC rainfall is above normal, the SST anomaly tends to be negative over the IO, the western MC, and the central-eastern tropical Pacific but positive from the eastern MC to the western North and South Pacific (Fig. 5a). This SST anomaly pattern is accompanied by an anomalous easterly flow to the east of MC and an anomalous westerly flow to the west of MC in the lower troposphere, inducing an anomalous cyclone near the Philippines. Anomalous cyclonic circulations over the southern and northern IO as a Rossby response to the enhanced heating over MC contribute to the anomalous westerly flow from the
equatorial IO to the west of the MC. Thus, low-level winds form an anomalous convergence over the MC. The anomalous cyclonic circulation and strong convergence near the Philippines enhance rising motion over the MC, favoring heavy rainfall. The structure of wind pattern suggests that increased rainfall over the MC is often related to a strengthened Walker circulation. The anomalous southerly flow over the North Pacific within 160°–180°E matches the result of Dayem et al. (2007), who showed that increased MC rainfall was related to a weak local Hadley cell to the east of MC. The variations of MC rainfall are also likely to affect East Asian rainfall via the local Hadley cell (100°–130°E), meaning that enhanced rising motion over MC is related to an enhanced sinking motion and thus reduced rainfall over East Asia (Fig. 5b). The robust teleconnection pattern revealed in Fig. 5 also shows that the variations of MC rainfall can even be related to the variations of rainfall over North America between 15° and 40°N.

For dry season, increased rainfall over MC is related to warm SST that extends from MC to the western South Pacific and cold SST over the central-eastern tropical Pacific (Fig. 5c), suggesting a negative influence of ENSO and a positive influence of SPCZ on MC rainfall (Aldrian and Susanto 2003). Anomalous westerly (easterly) wind is dominant over the equatorial IO (tropical western-central Pacific) and the tropical eastern North Pacific between 140° and 90°W. Cross-equatorial flow over the IO strengthens but the southwesterly flow from India to the Indo-China Peninsula weakens, with heavy rainfall forms over the Arabian Sea and the Bay of Bengal (Fig. 5d). On the other hand, the cross-equatorial flow over 120°–140°E weakens compared to the climatology (see Fig. 9), and the positive SST anomaly strengthens the convection over the surrounding regions of the Banda and Arafura Seas (Kubota et al. 2011), leading to positive rainfall anomaly. Besides, enhanced rainfall (convection) over the MC can induce an anomalous anticyclone and thus suppress rainfall over southeastern China (Jiang et al. 2015) but favor more rainfall to the north. Compared to the wet season, the relationships between MC rainfall variations and the climate anomalies over the Northern Hemisphere and the southern IO are weaker.

It should also be noticed from Fig. 5 that the variations of local SST and rainfall are spatially incoherent in the wet season, which may contribute to the small predictability of wet season MC rainfall (see detailed discussion in the next sections). In the western MC, SST and rainfall are negatively and significantly correlated in the wet season, suggesting an atmospheric forcing on local oceans. As reported by Neale and Slingo (2003), the rainfall around Sumatra and Borneo is poorly correlated with the rainfall over other areas of the MC. Interestingly, a small area in northern New Guinea also shows an insignificant feature. Moreover, the MC rainfall varies in phase with the rainfall over Australia for both seasons. In the wet season, an anomalous cyclonic (anticyclonic) circulation over the southern IO enhances (suppresses) rainfall over northwestern Australia. However, the MC rainfall is more significantly correlated with the rainfall over eastern Australia in the dry season. Since the wet and dry seasons are defined as December–March and July–October, respectively, it can also be claimed that Figs. 5a and 5b show the features of the peak and decaying phases of La Niña while Figs. 5c and 5d present the features of the developing phase of La Niña.

Given the features shown in Fig. 5, we further conduct a partial correlation analysis to separate the effect of ENSO on MC rainfall. Figure 6 shows that when ENSO influence is excluded, the negative correlation between MC rainfall and the SST over the tropical IO and Pacific almost disappears for both wet and dry seasons. The anomalous easterly flow over the east of MC and the anomalous westerly flow to the west still exist but have smaller magnitudes, suggesting an independent effect of MC rainfall on the Walker circulation. For the wet
season, the positive correlation between MC rainfall and the SST over the Pacific north of 20°N disappears and the strong anomalous anticyclonic circulation over the North Pacific turns to a weak cyclonic circulation, but the anomalous cyclonic circulations over the northern and southern IO and near the Philippines still exist although their magnitudes become smaller (Fig. 6a). Interestingly, the positive rainfall–SST correlation over the South Pacific is even more significant (Fig. 6a), but the positive correlation between MC rainfall and the rainfall over the east of Australia becomes much weaker and the associated anomalous winds diminish as well (Fig. 6b). The feature suggests that in the wet season the rainfall east of Australia is mainly modulated by ENSO instead of local SST. Additionally, while the MC rainfall is still highly correlated with the rainfall and winds over East Asia, the negative rainfall–SST correlation over western MC disappears. This feature suggests that the variation of wet season rainfall over western MC is partly related to the variation of EAWM, which exerts an important impact on the deep convection over MC (e.g., Chang and Lau 1982; Chang et al. 2005b), although there is no strong northeasterly wind over the South China Sea. A strong EAWM triggers convection over the MC by frequent cold surges, which originate from the high latitudes and weaken over the tropics (Chang et al. 2005a). The coefficient of correlation between the wet season rainfall over the western MC (15°S–10°N, 95°–120°E) and the EAWM index is as high as 0.70. Although the coefficient drops to 0.51 when ENSO signal is removed, it still significantly exceeds the 99% confidence level.

For the dry season, a narrow band of positive correlation between MC rainfall and SST is seen around the MC (Fig. 6c), indicating a combined effect of local SST and ENSO on the variation of dry season MC rainfall. Besides, the winds over East Asia are stronger in Fig. 6c than in Fig. 5c. The above analysis indicates a close connection between the MC and the ENSO system.
relationship between MC rainfall and the climate anomalies over East Asia.

Figure 7 shows the patterns of correlation between MC rainfall indices and previous SST and regression of previous 850-hPa winds against MC rainfall indices. For example, Fig. 7a shows average of correlations of wet season MC rainfall with the SSTs in November, December, January, and February, respectively. The most dominant feature is that the signals of the dry season decrease more rapidly as lag time increases, compared to those of the wet season. This feature is strongly related to the life cycle of ENSO, which usually begins before the dry season and ends after the wet season.

4. Simulation of MC rainfall variations by CFSv2

Comparison of the monthly means of MC rainfall between observation and CFSv2 of 0-month lead indicates that the forecast system well captures the annual evolution of MC rainfall, especially for the values in May and July (Fig. 8). However, although the CFSv2 reproduces the heavy rainfall in wet months and the light rainfall in dry months as observed, the magnitude of the annual variation of MC rainfall is underestimated due to dry biases from October to June and wet biases in August and September.

Figure 9 shows the climatology of rainfall and 850-hPa winds for observations and the ensemble mean of 0-month lead hindcast. In the wet season, the MC rainfall is described by three rainfall centers over the west of Sumatra, between Borneo and Java, and to the south of New Guinea (Fig. 9a). Northeastery flow prevails over areas north of the equator while westerly flow is dominant over areas south of the equator, favoring heavy rainfall in between. For the dry season, the westerly flow over southern MC is replaced by strong southeasterly wind, while the northern MC is dominated by southerly flow, forming a convergence over the northern MC (Fig. 9b). Thus, a zonally orientated rainband is located over the northern MC and a meridionally orientated rainband stretches from 8°S to 25°N over the western MC. In the meantime, the southern MC receives light rainfall. The hindcast shows similar features of MC rainfall and associated winds such as the direction and
location of the rainband and the direction of the winds (Figs. 9c,d). However, the model underestimates the rainfall between Borneo and Java and over the south of New Guinea, along with the westerly flow over the southern MC in wet season. In contrast, the rainfalls over the two sides of MC are overestimated (Fig. 9c). A more realistic pattern is simulated by the CFSv2 for the dry season, but a remarkable wet bias is found around New Guinea (Fig. 9d). Meanwhile, the band of heavy rain to the west of MC stretches too far to the western IO, and the rainfall over the eastern Arabian Sea is overestimated as reported by previous studies (e.g., Yang et al. 2008b; Jiang et al. 2013b). The overestimated rainfall over the northern IO is associated with underestimated SST over the western part of the northern IO and overestimated SST over the Bay of Bengal and the SCS (not shown), leading to weaker-than-observed southwesterly wind that favors more moisture over the northern IO.

Figure 10 shows that the CFSv2 also captures the interannual variations of MC rainfall associated with El Niño and La Niña events, implying the importance of ENSO for CFSv2 prediction. The coefficient of correlation between observed and simulated MC rainfall indices is 0.89, exceeding the 99% confidence level, for both wet and dry seasons. However, differences are also seen between the observations and the predictions. For example, the MC rainfall in wet season is generally underestimated especially after 2000 (Fig. 10a). On the contrary, the model overestimates MC rainfall in most of the dry seasons (Fig. 10b).

We further investigate the simulated relationships between MC rainfall and large-scale climate anomalies. Figure 11, which shows correlation and regression patterns for 0-month lead, indicates that the CFSv2 patterns are highly similar to the observed (see Fig. 5). For the wet season, the CFSv2 reproduces the negative–positive–negative patterns related to large-scale SST and rainfall features, even including the insignificant features around Sumatra and Borneo (Figs. 11a,b). The observed wind patterns are also well captured, such as the anomalous winds over the equatorial regions, the anomalous cyclonic circulations over the northern and southern IO and near the Philippines, and the anomalous anticyclonic circulations over the North and South Pacific. The patterns over the tropics in the dry season are particularly
well reproduced. However, the relationships of MC rainfall with large-scale features over Asia, the IO, and the North Pacific are stronger than observed for both wet and dry seasons, indicating an overestimation of ENSO impact as discussed by Yang et al. (2008b), Hu et al. (2013), and Jiang et al. (2013b). Overall, the CFSv2 simulates the relationships between MC rainfall and climate anomalies more realistically over the tropics than over the extratropics.

5. Prediction of MC rainfall in different leads

Figure 12 shows the monthly means of MC rainfall predicted by CFSv2 for different leads. It can be seen that the prediction of dry season rainfall is more sensitive to initial conditions than the prediction of wet season rainfall. The dry season integrations use the initial conditions of spring and early summer when the state of oceans and atmosphere varies remarkably with time. Moreover, comparison between Fig. 2 and Fig. 12 indicates that the MC rainfall in wet months is underestimated in almost all leads.

Figure 13 presents the differences in rainfall and 850-hPa winds between CFSv2 of 1-month lead and observations, and between different leads. An analysis of the differences between 1-month lead and observations (Figs. 13a,f) shows that, for the wet season, dry biases appear over Malay, Sumatra, Borneo, and the adjacent oceanic regions (Fig. 13a). The rainfall over northeastern MC and the southwest of Sumatra is overpredicted and the 850-hPa winds over southern MC are weaker than observed. For dry season, a dry bias is found over central MC but a wet bias is seen over northern MC (Fig. 13f). Differential westerly wind appears over the equatorial regions from the western IO to the western Pacific.

As shown in Figs. 13b–e (for the wet season) and Figs. 13g–j (for the dry season), the predictability errors, defined as the differences between two model predictions according to Drbohlav and Krishnamurthy (2010), vary in different leads. For difference between 3-month lead and 1-month lead, excessive rainfall and a cyclonic circulation appear over the southwest of Sumatra while deficient rainfall and an anticyclonic circulation (or a divergence) are seen around the Philippines in both wet and dry seasons (Figs. 13b,g). From 3-month lead to 5-month lead, a dry bias (divergent wind) and a wet bias (cyclonic circulation) appear over northeastern MC and west of the Philippines respectively in the wet season (Fig. 13e). However, deficient rainfall along with a divergence is seen over most of MC in the dry season (Fig. 13h). After the 5-month lead, changes become much smaller, except for the difference between 9-month lead and 7-month lead, in the wet season. Overall, the predictability errors are larger in the dry season than in the wet season when the lead time is less than 5 months, suggesting that the prediction for dry season rainfall is more sensitive to the initial conditions of the first few months than for the wet season. Additionally, comparison between the prediction errors (differences between observations and hindcast predictions) and the predictability errors indicate that prediction errors mainly come from the deficiencies of the model (see also Jiang et al. 2013b).

Figure 14a presents the correlations of observed MC rainfall with predicted rainfall by CFSv2, observed Niño-3.4, and predicted Niño-3.4 for different time leads. The CFSv2 is highly skillful in predicting the interannual variability of MC rainfall for both wet and dry seasons, with values of correlation coefficient exceeding the 95% confidence level ($R = 0.37$ according to the Student’s $t$ test) for all leads. For dry season, the coefficients of correlation between observed and CFSv2 predicted rainfall even exceed the 99% confidence level ($R = 0.49$) for all leads. The model prediction skill decays gradually from 1-month to 7-month lead, with a largest decrease from 4-month to 5-month lead. The coefficients of correlation between MC rainfall predicted
by Niño-3.4 (both in observation and CFSv2) and observed MC rainfall are lower than those of MC rainfall predicted by CFSv2 and observed MC rainfall for all time leads in dry season. The prediction skill for predicted Niño-3.4 is higher than that for observed Niño-3.4 when lead time is longer than 2 months. For the wet season, the prediction skill of CFSv2 decreases rapidly from 0-month to 2-month lead and then changes slightly with lead time.

FIG. 13. (a), (f) Changes in rainfall (mm day$^{-1}$, shading) and 850-hPa winds (m s$^{-1}$, vectors) for observations and hindcast ensemble mean of 1-month lead. Also, shown are changes in hindcast rainfall and 850-hPa winds for different lead months: differences between (b), (g) 3-month and 1-month leads, (c), (h) 5-month and 3-month leads, (d), (i) 7-month and 5-month leads, and (e), (j) 9-month and 7-month leads. Information is shown for both the (left) wet and (right) dry season.
(consistent with the feature shown in Figs. 13b–e); however, the prediction skill of CFSv2 for the wet season is lower than that for the dry season at all leads. On the other hand, the prediction skill of Niño-3.4 (both in observations and in CFSv2) is generally higher than that of CFSv2 when the lead time is longer than 0 months in the wet season. These analyses indicate that the CFSv2 has a large bias in simulating the response of wet season MC rainfall to ENSO. The model is skillful for predicting the MC rainfall of dry season and it has a potential to predict the rainfall in the wet season when the predicted SST is used reasonably. Figure 14b, which depicts the monthly correlation between CFS predicted rainfall of different leads and observed rainfall, shows higher prediction skills for August–November (generally dry months) and lower prediction skills for December–February (wet months), April, and June.

We further analyze the model’s skill in predicting the large-scale climate features that are related to MC rainfall variations. Figure 15 shows correlation (regression) of SST and rainfall (850-hPa winds) from the hindcast with (against) observed rainfall indices. Overall, patterns of prediction do not vary significantly with lead time, as do those in Fig. 11. The model captures the major features of anomalous rainfall, SST, and 850-hPa winds for all leads. However, for wet season, the relationship between MC rainfall index and the rainfall over western MC especially around Sumatra and Borneo is unrealistically predicted (Figs. 15a–d). The rainfall around Sumatra and Borneo is poorly correlated with the rainfall over other MC regions in observation, but the correlation is significantly negative in CFSv2 predictions. Correspondingly, the anomalous cyclonic circulation over the IO is weaker in the long leads, producing weaker-than-observed convergence over the western MC and the IO, and the relationship between MC rainfall and the rainfall over the IO is underestimated. This feature agrees with the result of Neale and Slingo (2003), who showed that the rainfall bias over MC could be a driver for other systematic errors and the bias of the Walker circulation could be responsible for those systematic errors over the tropics. In addition, previous studies (Kim et al. 2014; Wang et al. 2014) have shown that the MJO, which is most prominent in boreal winter, is a major potential source of climate predictability on subseasonal time scales. However, the CFSv2 has a difficulty in predicting the propagation of the MJO across the MC (Kim et al. 2014; Wang et al. 2014). Thus, we assume that the model has a difficulty in predicting the MJO-related anomalies over
MC, which contributes to the lower prediction skill of MC rainfall after 0-month lead in wet season.

Although there is a strong link between MC rainfall and ENSO in observations, several forecast systems have predicted opposite relationships between ENSO and western MC rainfall in boreal winter (e.g., Luo et al. 2005; Jiang et al. 2013c). Here, we further analyze the relationships between ENSO and predicted rainfall
focusing on the regional features of MC rainfall. As shown in Fig. 16, for dry season, the CFSv2 captures the anomaly patterns including the positive correlation for rainfall over the entire MC region, the anomalous westerly wind over the equatorial IO, and the anomalous easterly wind over the equatorial Pacific. For wet season, although the anomalous cyclonic circulations over the northern and southern IO and near the Philippines are...
well reproduced, apparent errors of rainfall prediction are seen around Sumatra, Malay, and Borneo (SMB). These errors even worsen as lead time increases (Figs. 16a–d). Thus, although the dry season prediction is more sensitive to initial conditions as shown above, the prediction errors of rainfall around SMB, their worsening with lead time, and the unrealistic rainfall–circulation relationship predicted by CFSv2 account for the relatively lower prediction skill for wet season MC rainfall.

The prediction skill for rainfall over 8°S–5°N, 100°–118°E (i.e., SMB) and the correlation between negative Niño-3.4 SST and SMB rainfall for different leads are shown in Fig. 17. For comparison, the correlation for the eastern MC (EMC) is also shown. As seen from Fig. 17a, for dry season the prediction skill for SMB rainfall is similar to that for EMC rainfalls. However, for wet season the prediction skill for SMB rainfall is far below the 95% confidence level except in 0-month lead. That is, in the wet season, the prediction skill for SMB rainfall is much lower than that for EMC rainfall, although the skill for EMC rainfall is lower in the wet than in the dry season. Correspondingly, the correlation between negative Niño-3.4 SST and SMB rainfall in dry season is high in observation ($R = 0.6$) and is well reproduced by CFSv2 for all time leads. In contrast, the positive correlation for the wet season becomes negative in predictions. On the other hand, the correlation between negative Niño-3.4 SST and EMC rainfall is strong for both wet and dry seasons (in observation, $R = 0.81$ for the dry season and $R = 0.86$ for the wet season) and it is well predicted. This result indicates that the low prediction skill for wet season MC rainfall is contributed mainly by the low skill for SMB rainfall prediction, and the low skill for wet season SMB rainfall can be partly due to the unrealistically predicted relationship between SMB rainfall and ENSO.

6. Conclusions and discussion

We have analyzed the seasonal to interannual variations of rainfall over the Maritime Continent and their relationships with large-scale climate anomalies. We have also discussed the predictability and prediction of MC rainfall focusing on regional features and the roles of ENSO and the Asian-Australian monsoon circulation.
The rainfall over MC is clearly characterized by a wet season from December to March and a dry season from July to October, and it exhibits remarkable interannual variability in each season. For both wet and dry seasons, the extremely dry years and wet years match with El Niño and La Niña events, respectively. When the ENSO signal is removed, the interannual variations of MC rainfall are still apparent but their magnitude becomes much smaller, indicating that the variations of MC rainfall are also modulated by other factors.

In the wet season, the variations of MC rainfall exhibit the atmospheric and SST features of ENSO peak-decaying phases, and SST and rainfall variations are spatially incoherent. This spatial incoherence leads to low predictability of the wet season MC rainfall. In the dry season, the variations of MC rainfall resemble the features of the ENSO developing phase, and the atmospheric interaction between MC and the extratropics appears to be insignificant compared to that in the wet season. When ENSO influence is excluded, the MC rainfall is highly correlated with the rainfall and 850-hPa winds over East Asia.

Many features of the MC rainfall, including the mean annual cycle, interannual variations, and the relationship between the rainfall and large-scale climate patterns are well simulated by the NCEP CFSv2. However, the wet season rainfall around Sumatra and Borneo and over the south of New Guinea is underestimated, and the dry season rainfall over New Guinea is overestimated. The CFSv2 predicts the relationship of MC rainfall with tropical climate patterns more realistically compared to the relationship with extratropical patterns. Overall, the model overestimates the impact of ENSO on MC rainfall.

The prediction of dry season rainfall is more sensitive to initial conditions, since the integrations use the initial conditions of spring and early summer when the state of oceans and atmosphere experiences remarkable changes. However, the prediction skill is much lower for the wet season when the model unrealistically predicts the variations of rainfall around Sumatra and Borneo. This lower skill is also partly due to the unrealistically predicted relationship between ENSO and the local rainfall for the wet season.

Since ENSO plays an important role in predicting MC rainfall, we further conduct an analysis of the skills of MC rainfall prediction for various leads as a function of ENSO amplitude (Kim et al. 2012a,b). It can be seen from Fig. 18 that the prediction skills change apparently from

---

**Fig. 18.** Anomaly pattern correlation for the MC region in the (a) wet and (b) dry season for different lead months. The gray bar represents the ENSO amplitudes for the wet season and dry season.
one year to another for both wet and dry seasons. Overall
the CFSv2 has higher predictive skills for MC rainfall in
both seasons during strong ENSO years. Examples can
season and in 1987–88 and 1997–99 for the dry season.

Figure 19 further presents that the mean prediction
skills for MC rainfall increase with ENSO magnitude,
suggesting that the source of skill for MC rainfall comes
mainly from ENSO. For strong ENSO events, the pre-
diction skill is higher in dry season than in wet season.

When ENSO magnitude is less than 0.58, the skill for
predicting wet season MC rainfall beyond 1-month lead
does not show an apparent decrease, which may be re-
lated to the unrealistic relationship predicted between
the SMB rainfall and ENSO in this season. Additionally,
for all ENSO magnitudes the prediction skill for wet
season MC rainfall decreases quickly after 1-month lead,
while the prediction skill for dry season rainfall is similar
between 1-month and 3-month lead. This result is also
consistent with the features discussed in the above section.
It should be pointed out that in addition to ENSO, other factors such as model physics and ocean–land–atmosphere coupling processes must affect the performance of MC rainfall prediction as well. We are currently conducting an investigation into the performance of rainfall prediction for every year to understand different potential factors that lead to different prediction skills. Moreover, the prediction skills for MC rainfall must vary with time scales, and an analysis of the predictability of MC rainfall on subseasonal scales is being carried out.

Acknowledgments. The authors thank the three anonymous reviewers for the constructive comments on the earlier version of the manuscript. They also thank Prof. Francis Zwiers of the University of Victoria, Prof. Yi Deng of the Georgia Institute of Technology, and Prof. Mingfang Ting of Columbia University for a number of helpful discussions. This study was jointly supported by the National Key Research Program of China (Grants 41375081 and 91337107), the LASW State Key Laboratory Special Fund (2013LASW-A05), and the Special Funds of Guangdong Province (YCI2013-196).

REFERENCES


