Roles of Remote and Local Forcings in the Variation and Prediction of Regional Maritime Continent Rainfall in Wet and Dry Seasons

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ABSTRACT
Seasonal prediction of extratropical climate (e.g., the East Asian climate) is partly dependent upon the prediction skill for rainfall over the Maritime Continent (MC). A previous study by the authors found that the NCEP Climate Forecast System, version 2 (CFSv2), had difference in skill between predicting rainfall over the western MC (WMC) and the eastern MC (EMC), especially in the wet season. In this study, the potential mechanisms for this phenomenon are examined. It is shown that observationally in the wet season (from boreal winter to early spring) the EMC rainfall is closely linked to both ENSO and local sea surface temperature (SST) anomalies, whereas the WMC rainfall is only moderately correlated with ENSO. The model hindcast unrealistically predicts the relationship of the WMC rainfall with local SST and ENSO (even opposite to the observed feature), which contributes to lower prediction skill for the WMC rainfall. In the dry season (from boreal late summer to fall), the rainfall over the entire MC is significantly influenced by both ENSO and local SST in observations and this feature is well captured by the CFSv2. Therefore, the hindcasts do not show apparently different skill in rainfall prediction for EMC and WMC in the dry season. The possible roles of atmospheric internal processes are also discussed.

1. Introduction
The Maritime Continent (MC) lies within the warmest oceanic area, with heavy rainfall (Ramage 1968; Qian 2008), and it plays an important role in global atmospheric circulation (Sun et al. 2009; Jiang et al. 2015). The seasonal evolution of MC rainfall is characterized by a wet season and a dry season (e.g., Murakami and Sumi 1982; McBride et al. 2003; Hendon 2003; Chang et al. 2004; Jo and Ahn 2015). The variations of MC rainfall, as well as its relationship with ENSO and other atmospheric systems, differ with seasons and with areas within the MC (Nicholls 1981; Hastenrath 1987; Kiladis and Diaz 1989; Kirono et al. 1999; Hamada et al. 2002). Previous studies have demonstrated that the MC rainfall varies coherently and is highly correlated with ENSO during the dry season (e.g., Haylock and McBride 2001; McBride et al. 2003; Hendon 2003; Chang et al. 2005b; Gomyo and Koichiro

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In the wet season, rainfall over the MC (especially the western MC) is not highly correlated with ENSO, which may be due to the spatial incoherence of rainfall (Haylock and McBride 2001), local SST forcing that might cancel the ENSO influence (Hendon 2003), or complicated wind–terrain interaction during that season (Chang et al. 2004). Local and remote forcings play different roles in driving the rainfall anomalies over the MC during different seasons (Nicholls 1979, 1984; Rowell 2001). However, it is unclear to what extent these local and remote factors force the anomalies of regional MC rainfall.

Several studies have reported that the prediction skill for MC rainfall also varies among regions and seasons (e.g., Neale and Slingo 2003; Kirono et al. 1999; Jiang et al. 2013; Argueso et al. 2016). Within the MC, the Indonesian wet-season rainfall is inherently unpredictable (Haylock and McBride 2001). Multiple models have shown much lower skill in predicting theMC rainfall in the wet season compared to the dry season (e.g., Aldrian et al. 2007; Zhang et al. 2016). Over the years, scientists have made a great deal of effort to enhance representation of MC rainfall features in climate models, but large biases still exist (e.g., Gianotti and Eltahir 2014a,b; Schiemann et al. 2014). Moreover, few studies have paid attention to investigations of the factors that are responsible for the difference in prediction skill of regional MC rainfall.

The aim of this study is to understand the respective roles of remote and local forcings in the variation and prediction of regional MC rainfall in wet and dry seasons. Section 2 describes the model, data, and methods applied. Results are shown in section 3. A summary of the study and further discussion are provided in section 4.

2. Model, data, and methods

The National Centers for Environmental Prediction (NCEP) Climate Forecast System, version 2 (CFSv2), is a fully coupled dynamical prediction system. It consists of the NCEP Global Forecast System as its atmospheric component; the Modular Ocean Model, version 4.0, as the oceanic component; the NCEP, Oregon State University (OSU), Air Force Research Laboratory, and the NOAA/Office of Hydrology land surface model (Noah); and a three-layer interactive global sea ice model (Saha et al. 2014). Output of rainfall, surface temperature [ST, including sea surface temperature (SST) for oceans and surface skin temperature for land], and 850-hPa winds from the retrospective forecasts of 9-month integrations by the CFSv2 from 1983 to 2010 are analyzed. Details about the 9-month hindcast runs can be seen in Zhang et al. (2016). We calculate the ensemble mean of the 24 members as in Zhang et al. (2016). For convenience, the hindcast ensemble means at 0-month lead, 1-month lead, and so on to a 9-month lead are denoted as LM0, LM1, through LM9, respectively.

For model verification, rainfall from the Climate Prediction Center (CPC) Merged Analysis of Rainfall (CMAP) (Xie and Arkin 1997), SST from the National Oceanic and Atmospheric Administration (NOAA) Optimum Interpolation SST (OISST) (Reynolds et al. 2007), and 850-hPa winds from the NCEP Climate Forecast System Reanalysis (Saha et al. 2010) are used. Also, outgoing longwave radiation (OLR; daily mean) from the NOAA Advanced Very High Resolution Radiometer (AVHRR) (Liebmann and Smith 1996), and 925-hPa meridional wind (daily mean) from the NCEP–DOE Reanalysis-2 (Kanamitsu et al. 2002) are also used in this study.

The relationships between MC precipitation and other global and regional climate variations represented by various climate indices are also examined. The Niño-3.4 index, defined as the SST averaged over the area within 5°S–5°N and 120°–170°W, is used to represent ENSO variability. The cold surge index analyzed is defined as the following. A cold surge event occurs when the average 925-hPa meridional wind between 110° and 117.5°E along 15°N exceeds 8 m s⁻¹, following Chang et al. (2005a), and the number of cold surge events in boreal winter is calculated. The index for the Madden–Julian oscillation (MJO) intensity is also defined. First the OLR daily data were band-filtered with a 20–100-day 100-point Lanczos filter (see Slingo et al. 1999) and then the variance of the filtered MC OLR was calculated and averaged (for the wet season). In addition, a partial correlation analysis was applied as in Zhang et al. (2016). All datasets are analyzed for the period of 1983–2010.

3. Results

Following Zhang et al. (2016), the dry season and the wet season are defined as July–October and December–March, respectively. As shown in Figs. 1a and 1b, the CFSv2 shows high skill for the entire MC rainfall in the dry season and lower skill over parts of the MC, especially New Guinea and the western MC (WMC) in the wet season. Zhang et al. (2016) have reported a spatial incoherence of SST–rainfall relationship in the wet season, which shows a positive correlation over the eastern MC (EMC) and a negative correlation over the WMC. Thus, we conduct an analysis for the EMC (11°S–10°N, 120°–145°E) and WMC (13°S–7°N, 95°–120°E) separately in this study. The EMC (WMC) rainfall index
Fig. 1. Correlations of rainfall (mm day$^{-1}$) between observation and CFSv2 in 1-month lead for the (a) wet season and (b) dry season, and correlations between observation and CFSv2 predictions for area-averaged rainfall for the (c) WMC and (d) EMC. Values exceeding the 90%, 95%, and 99% confidence levels are shaded. The domains used to define WMC ($13^\circ$S–$7^\circ$N, $95^\circ$–$120^\circ$E) and EMC ($11^\circ$S–$10^\circ$N, $120^\circ$–$145^\circ$E) are outlined with black boxes in (a) and (b).

is defined as area-averaged rainfall over EMC (WMC). Figures 1c and 1d show the variations in skill of rainfall prediction as a function of calendar month and lead time (in months) over the EMC (Fig. 1c) and the WMC (Fig. 1d), respectively. The most noticeable feature in Fig. 1c is that the correlation coefficients for the WMC rainfall in July–November are above 0.6 and up to 5-month lead and that the correlation exceeding the 95% confidence level occurs at lead time longer than 8 months. However, the model’s skill is much lower in December–June, with the correlation passing the 95% confidence level only at 0-month lead. The prediction
skill for the EMC rainfall is also different between the wet and dry seasons, but the difference is not as remarkable as for the WMC. The model shows higher skill in predicting the WMC rainfall than the EMC rainfall in the dry season, but much lower skill in predicting the WMC rainfall than the EMC rainfall in the wet season. From the above analysis, one may ask the following question: what factors are responsible for the differences in the prediction skill between EMC and WMC?

a. Wet season

Variations of MC rainfall can be significantly modulated by ENSO and local SST (e.g., Hendon 2003; Chang et al. 2004; Zhang et al. 2016); however, it is still unclear how the two factors influence the rainfall variations since local SST anomalies tend to occur in conjunction with ENSO (Hendon 2003). As shown in Figs. 2a and 2c, the variations of rainfall over both the WMC and the EMC are significantly correlated with ENSO. The spatial patterns of ST correlation and 850-hPa wind regression with respect to WMC and EMC rainfall anomalies are remarkably similar to each other. However, the local ST–rainfall relationship is very different. The EMC rainfall is positively correlated with local ST, whereas negative correlation is seen between WMC rainfall and local ST. Besides, the interaction between ENSO-related winds (anomalous westerly winds over the Indian Ocean) and the terrain over WMC, which can be seen from the difference between the ENSO-related and the anomalous WMC land rainfall–related composite patterns of wind fields (figures not shown), leads to a more complicated relationship between ENSO and the rainfall over this region, consistent with study of Chang et al. (2004). This wind–terrain interaction, which is difficult for the model to capture, may result in lower prediction skill for the ENSO–rainfall relationship over the WMC region. When the ENSO influence is excluded, the WMC rainfall is uncorrelated with local ST while the EMC rainfall is still significantly correlated with the local ST (Figs. 2b,d).

To investigate the possible influences of local and remote forcings on EMC and WMC rainfall anomalies, we analyze the correlation of preceding Niño-3.4
indices and local ST with the WMC and EMC rainfall indices for the wet season (Table 1). While the WMC rainfall is significantly related to previous central-eastern Pacific SST (with lead time longer than 5 months), it is negatively correlated with local SST in the wet season and insignificantly related to previous local SST, suggesting that it is not forced by the local ST. On the other hand, the EMC rainfall is significantly correlated with both local SST and ENSO, also with lead time longer than 5 months. The influence of ENSO on the EMC rainfall is slightly stronger than that on the WMC rainfall.

Thus, the performance of CFSv2 in predicting the relationship of rainfall anomalies with remote and local forcings tends to have an impact on the skill of predicting local rainfall variations. Then, we compare these relationships in observations and the CFSv2. As an example, the correlations between rainfall and ST anomalies in January for observation and CFSv2 hindcasts are shown in Figs. 3a–d. The most remarkable difference is that the

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Fig. 3. Correlations between ST and rainfall in January for (a) observation, and hindcast ensemble mean of (b) 0-month lead, (c) 1-month lead, and (d) 4-month lead. Coefficients of correlation between ST and rainfall over the (e) WMC and (f) EMC in the wet-season months. R12, R1, R2, and R3 represent correlation coefficients in observation for December, January, February, and March, respectively. Black, red, green, and blue lines represent the correlation coefficients in hindcast ensemble mean of different leads for December, January, February, and March, respectively. Values that significantly exceed the 90%, 95%, and 99% confidence levels are shaded in (a)–(d). Straight dotted line in (e) and (f) denotes the 90% confidence level. The domain of WMC and EMC are outlined with black boxes in (a)–(d).
correlation between ST and rainfall over the WMC in model is opposite to that in observation. Moreover, the model overestimates the ST–rainfall relationship over the EMC. As seen from Fig. 3e, the model predicts significant positive correlations (opposite to those observed) between ST and rainfall over the WMC after LM0 for January and after LM3 for February and March, and the ST–rainfall relationship is also unrealistically predicted after LM1 for December. The ST–rainfall relationship over the EMC is overestimated in December and underestimated in March for all leads (Fig. 3f). The model also unrealistically predicts the ST–rainfall relationship over the EMC in January and February (Fig. 3f). The relationships between ENSO and WMC rainfall are unrealistically predicted for all wet-season months (the correlations between previous ENSO indices and wet-season WMC rainfall indices are also unrealistically predicted), while the model predicts the relationship between ENSO and EMC rainfall well, despite a slight overestimation (figure not shown). Consistently, the model unrealistically predicts the interaction between ENSO-related winds and the terrain over WMC after LM1 (figure not shown).

b. Dry season

Rainfall variations over the WMC and the EMC are both significantly correlated with ENSO in the dry season (Figs. 4a,c). When the ENSO influence is excluded, the WMC rainfall is still significantly correlated with local ST (Fig. 4b). However, signals almost disappear for the EMC rainfall, implying that the rainfall variation over EMC is mainly modulated by ENSO (Fig. 4d).

The values shown in Table 1 in the dry columns are the correlation coefficients for the dry season. Rainfall variations over the WMC are significantly related to ENSO and local ST by 3 months in advance. The EMC rainfall can be significantly forced by ENSO, also by 3 months in advance, but is only significantly related to local ST by 1 month in advance. These results are consistent with the above analysis.

As an example, we show in Figs. 5a–d the correlations between rainfall and ST in October for observations and the CFSv2. For the entire MC, the rainfall–ST relationships are well predicted in various lead months, although they are slightly overestimated. Unlike in the wet season, the model realistically predicts the relationship between rainfall and ST over WMC in the dry season for all leads, and the correlation coefficients in the model are close to those in observations (Fig. 5e). Moreover, the ST–rainfall relationship over EMC are well predicted in the dry season, although they are underestimated by the model (Fig. 5f). The relationships
of WMC and EMC rainfall with ENSO in the dry season are also well predicted in the model for all leads (also the correlations of previous ENSO indices with dry-season WMC and EMC rainfall indices are realistically predicted as well), despite some overestimations (figure not shown).

4. Discussion and conclusions

The roles of remote forcing and local boundary forcing in the variations and prediction of regional MC rainfall in wet and dry seasons are investigated. Rainfall averaged over the EMC (11°S–10°N, 120°–145°E) and the WMC (13°S–7°N, 95°–120°E) are studied separately because of the different physical mechanisms for rainfall variations over the two regions.

In the wet season, the rainfall over both WMC and EMC are significantly forced by the central-eastern Pacific SST at least 5 months in advance. The EMC rainfall variation is also significantly related to local boundary forcing at least 5 months in advance; however, the WMC rainfall is insignificantly influenced by local boundary forcing. The CFSv2 unrealistically predicts the relationship of WMC rainfall with ENSO and local boundary forcing (the wind–terrain and air–sea interactions are also unrealistically predicted; figures not shown) for all wet-season months when lead time is longer than 1 month, contributing to the poor skill in predicting the WMC rainfall. On the other hand, the model predicts the relationship between ENSO and EMC rainfall well, although the relationship between the rainfall and local boundary forcing is unrealistically predicted, leading to higher prediction skill for the rainfall over EMC compared to WMC in the wet season. We have also examined these relationships in the ensemble members of CFSv2 and obtained similar features.

For the dry season, the WMC rainfall is significantly related to ENSO and local boundary forcing at least 3 months in advance. However, the EMC rainfall is mainly modulated by ENSO. The relationships of ENSO and local boundary forcing with both WMC and EMC rainfall are well predicted by the NCEP model, leading to higher prediction skill of rainfall over the entire MC in the dry season. Moreover, the linkage between the skill of rainfall prediction and the relationship of rainfall with local SST implies that over tropical regions the skill of rainfall prediction is low.

Fig. 5. As in Fig. 3, but for October in (a)–(d) and for the dry-season months, July–October (with correlation coefficients R7–R10), in (e) and (f).
where the influence of SST is weak, and vice versa (also see Kumar et al. 2013).

In this study, we have mainly focused on the roles of external forcing. However, rainfall is also affected by atmospheric internal processes. Previous studies have reported that cold surges and MJO contribute to the variability of convection or rainfall over the MC (e.g., Lau et al. 1983; Chang et al. 2005a). In addition, previous studies have demonstrated deficiencies of climate models in reproducing the MJO-related variability over the MC (e.g., Seo et al. 2009; Weaver et al. 2011; Kim et al. 2014). Can MJO and cold surges influence the interannual variability of rainfall over the MC? The correlation between cold surges and the rainfall in boreal winter shows that both the EMC rainfall and the WMC rainfall are significantly correlated to cold surges (figure not shown), with a coefficient of 0.68 (0.65) for EMC (WMC). This feature implies that cold surges may not be responsible for the difference in skill between the CFSv2 prediction of EMC and WMC rainfall. The interannual variability of observed rainfall over both EMC and WMC is not significantly related to MJO in the wet season and this feature in CFSv2 hindcast is not thus not analyzed (also because of the short data record in the model output). The influence of atmospheric internal processes on MC regional rainfall prediction needs to be further studied. Furthermore, the problem of poor model performance for the wet-season WMC rainfall is not limited to the NCEP model. The complicated relationship (or poor correlation) between WMC rainfall and ENSO, which may be due to the lack of internal spatial coherence of rainfall, the rapid change in the sign of local SST anomalies once the wet season commences, and the complicated air–sea and wind–terrain interactions over the WMC during the wet season, is difficult for models to capture (Haylock and McBride 2001; Hendon 2003; Chang et al. 2004; Zhu and Shukla 2013; Zhu and Shukla 2016). Thus, higher resolution and better representation of air–sea coupling process in models are important for the prediction of MC rainfall, especially the WMC rainfall.

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REFERENCES


