Chapter 25

Progress and Status of MJO Simulation in Climate Models and Process-Oriented Diagnostics

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Despite its tremendous influence on extreme weather worldwide, realistic simulations of the Madden–Julian oscillation (MJO) have been a grand challenge for global climate models. In the first part of this chapter, a brief overview of recent advances in modeling the MJO is provided by particularly highlighting improved MJO simulations achieved through implementations of stochastic cumulus approaches. In the second part, the most recent community efforts in the development of process-oriented diagnostics and metrics for MJO simulations are briefly reviewed. These diagnostics and metrics have been built upon the process understanding of key MJO physics, providing important guidance to expose critical model deficiencies in simulating the MJO. These processes include convective sensitivity to environment moisture, convection–circulation interactions, cloud–radiation feedbacks, and large-scale control (e.g., the lower-tropospheric mean moisture pattern).

1. Introduction

The Madden–Julian oscillation (MJO, Madden and Julian 1971, 1994) plays a crucial role in the earth's hydrological cycle (Lau and Waliser 2012) by exerting tremendous influence on global climate and weather extremes over both tropical and extra-tropical regions (Zhang 2013). Due to its quasi-periodic behavior on intraseasonal timescales, the MJO represents one of the primary predictability sources for short-term climate prediction (Vitart *et al.* 2012; NAS 2016) and provides a fundamental basis for "seamless prediction" (e.g., Hoskins 2013). However, the MJO remains poorly represented in most of our latest generation global climate models (GCMs; Hung *et al.* 2013; Jiang *et al.* 2015; Ahn *et al.* 2017). For the limited number of GCMs that are able to capture the bulk characteristics of the MJO, the reasons for their good MJO simulations are also not well understood (e.g., Klingaman *et al.* 2015a). The poor model capability in representing the MJO leaves us great disadvantages in projecting future activity of weather and climate systems that are significantly modulated by the MJO.

The great challenges in simulating the MJO pose an urgent need for improvement in understanding the fundamental physics of the MJO. Most recently, great efforts have been undertaken in the community on process-oriented diagnosis of GCMs, aimed at identifying critical

The Multiscale Global Monsoon System
Edited by C. P. Chang et al.

processes that discriminate good MJO models from poor ones. For example, development of the process-oriented MJO metrics is one subproject of the WGNE MJO Task Force[1] and the NOAA's Climate Program Office Model Diagnostics Task Force.[2] The results of these process-oriented diagnoses are expected to inform changes of model parametrizations that are desirable for improved MJO simulations (e.g., Kim *et al.* 2009; Waliser *et al.* 2009; Sperber and Kim 2012; Wheeler and Maloney 2013; Kim *et al.* 2014).

This chapter briefly reviews advances in modeling the MJO using GCMs, with a specific focus on recent modeling development that applies a stochastic convection parameterization approach, and progress in developing process-oriented diagnostics for MJO simulations.

2. Progress of MJO Simulation in Climate Models

Many previous modeling studies suggested that simulations of the MJO are sensitive to model representation of subgrid cumulus processes. For example, improved MJO simulations can be achieved by inhibiting deep convection in model cumulus schemes through enhanced cumulus entrainment rate or increased rain reevaporation (see a review by Kim and Maloney 2017). However, the improved MJO representation achieved by tuning these parameters in model cumulus schemes often occurs at the cost of degraded model mean state and other climate phenomena (e.g., Kim *et al.* 2011). To avoid this issue and to comprehensively improve climate simulations including the MJO, explicit cloud-resolving models (CRMs) have been implemented in global models by either adopting a super-parameterization approach (Khairoutdinov and Randall 2003; Randall *et al.* 2003), i.e., replacing the model cumulus parameterization with a vertical 2D CRM, or expanding high-resolution CRMs over the global domain (Miura *et al.* 2007; Satoh *et al.* 2008). While success of this CRM approach for improvement of MJO simulations has been widely reported, even these CRM models could have substantial mean state biases (e.g., Stan *et al.* 2010; Kim *et al.* 2011). Moreover, due to the required large computing resources, currently it is not practical to extensively employ CRMs for climate projection studies that need long-term integrations with multiple ensemble members, although the super-parameterized GCMs have been used to understand MJO characteristics under idealized or perturbed climate (e.g., Pritchard and Yang 2016; Wolding *et al.* 2017).

While largely we have observed limited progress in improving MJO simulations in GCMs since the last IWM-V in Macao, in 2013 (see review chapters for the IWM-V workshop by Kim and Maloney 2017; Klingaman *et al.* 2017), one recent noteworthy development is the implementation of the stochastic convective parameterization approach in GCMs (e.g., Deng *et al.* 2015; Deng *et al.* 2016; Wang *et al.* 2016; Goswami *et al.* 2017a, b; Peters *et al.* 2017), based on the earlier stochastic modeling concept by introducing subgrid cumulus variability into deterministic parameterization scheme-based coarse-resolution GCMs (e.g., Buizza *et al.* 1999; Lin and Neelin 2003). One of these stochastic convective schemes, the stochastic multi-cloud model (SMCM), which was first developed and tested based on idealized frameworks (e.g., Khouider *et al.* 2010; Frenkel *et al.* 2013) and aqua-planet global atmospheric models (Deng *et al.* 2015), has been recently implemented to several different GCMs with full complexity (Goswami *et al.* 2017b, a; Peters *et al.* 2017). The SMCM is constructed

[1] http://wgne.meteoinfo.ru/activities/on-going-activities/wgne-mjo-task-force/.
[2] http://cpo.noaa.gov/Meet-the-Divisions/Earth-System-Science-and-Modeling/MAPP/MAPP-Task-Forces/Model-Diagnostics-Task-Force.

on rectangular lattices within each GCM grid to mimic the observed life cycle of organized tropical convective systems (e.g., Johnson *et al.* 1999; Mapes *et al.* 2006). Each element of the lattice is characterized either by one particular cloud type (congestus, deep, or stratiform) or clear sky conditions. Transition probabilities from one cloud type to another as well as formation and decay rates of different cloud types are linked to large-scale conditions, such as mid-tropospheric moisture and vertical velocity, and convective available potential energy (CAPE), depicting interactions between clouds at each lattice and their large-scale environment. The fraction of each cloud type within each GCM grid can then be obtained by a Markov stochastic process on each lattice, and total heating and drying effects by cumulus processes can be derived by prescribed Q_1 and Q_2 profiles associated with each cloud type.

By replacing the cumulus parameterization scheme with the SMCM in the Climate Forecast System version 2 (CFSv2, i.e., CFS–SMCM), improved simulations of both convectively coupled equatorial waves (CCEWs) and the MJO are obtained (Goswami *et al.* 2017a,b). In particular, both the MJO's eastward propagation beyond the Maritime Continent during boreal winter and its northward propagation during boreal summer over the Asian monsoon region are much improved in the CFS–SMCM (Goswami *et al.* 2017b). Note that cloud–radiation feedbacks have not been taken into account in this version of CFS–SMCM, which suggests a potential for further improvement of the MJO and CCEWs when using this SMCM approach in GCMs.

In another recent implementation of the SMCM to the convection parameterization of the ECHAM6.3 (Peters *et al.* 2017), an SMCM-based closure for deep convection triggering on a large-scale environment, such as vertical velocity and relative humidity at 500-hPa, was used to replace the standard CAPE-based closure in the original ECHAM6.3 (Nordeng 1994). Despite this simple implementation of SMCM, the eastward propagation of the MJO is also significantly improved in ECHAM6-SMCM over the original ECHAM6.3.

Compared to the conventional ways of tuning parameters in the convection schemes, one advantage of this SMCM approach is that the dominant parameters affecting model MJO variability tend to be different from those controlling the model mean state (Goswami *et al.* 2017a, Peters *et al.* 2017). Therefore, unlike the known parameter tuning strategies that give an improved MJO at the expense of the mean state, good model mean state can be largely retained in the CFS-SMCM and ECHAM6-SMCM along with improved MJO simulations (Goswami *et al.* 2017b, a; Peters *et al.* 2017). However, a drawback of the SMCM implementation to GCMs is the complicated calibration process of the SMCM which involves many parameters in depicting transition probability among different cloud types. While the model MJO simulations are sensitive to these parameters, such as the stratiform cloud decay timescale, many of these parameters are subject to observational constraints. Additionally, plausible dependence of these parameters on the large-scale environment needs to be considered, particularly for climate projection studies.

Another form of a stochastic convection scheme was also recently implemented in the National Center for Atmospheric Research (NCAR) atmospheric community model CAM5 (Wang *et al.* 2016). This stochastic approach was based on the one proposed by Plant and Craig (2008) that used a Poisson distribution for the number of plumes in a convective ensemble conditional on the CAPE and an exponentially distributed cloud base mass flux based on the theory of equilibrium statistical mechanics. It was shown that the PDF of precipitation intensity and the MJO eastward propagation are significantly improved by adding stochastic nature to the deep convection scheme. While there is still great room for improvement in the stochastic convection schemes described above, these initial results suggest great potential for improvement of MJO representation with stochastic cumulus schemes, which could serve as a less computationally expensive alternative to the CRM approach in representing subgrid cumulus variability.

3. Process-oriented Metrics for the MJO

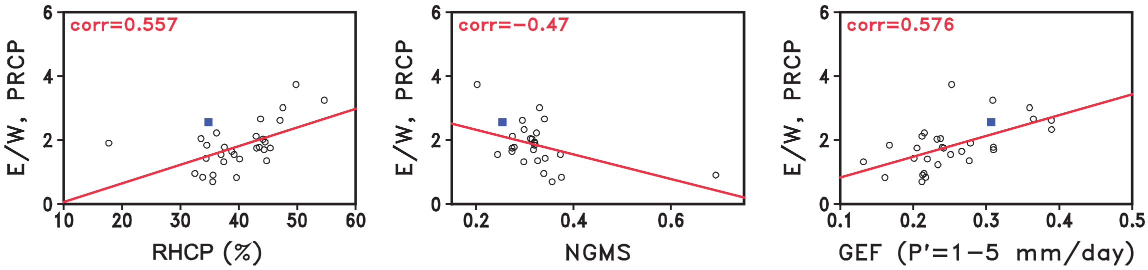
The strategy of the process-oriented diagnosis for the MJO is first to come up with a scalar measure for processes that are suggested to be important in simulating the MJO, i.e., process-oriented metrics, and then to examine the relationship between these process-oriented metrics and an MJO fidelity score in multi-model simulations. A robust relationship between a process-oriented metric and the MJO fidelity score suggests that the corresponding process is likely a key process operating in the group of models that contributes to their MJO simulation fidelity. These metrics that depict important processes for the MJO can help diagnose process-level model deficiencies and thereby help guide improvement in specific model parameterization schemes toward improving MJO simulations. Motivated by various observational, modeling, and theoretical studies on the MJO, several process-oriented metrics for the MJO have been recently proposed, including diagnostic metrics of the Relative Humidity Composite based on Precipitation (RHCP) (Kim *et al.* 2014; Ahn *et al.* 2017), the Normalized Gross Moist Stability (NGMS; Benedict *et al.* 2014; Jiang *et al.* 2015; Ahn *et al.* 2017), the mean lower-tropospheric moisture pattern (Gonzalez and Jiang 2017; Jiang 2017), the Greenhouse Enhancement Factor (GEF, Kim *et al.* 2015; Ahn *et al.* 2017), vertical moistening profiles as a function of rain rate (Klingaman *et al.* 2015a, b), and the convective moisture adjustment timescale (e.g., Jiang *et al.* 2016). In this section, we provide a brief review of these metrics.

3.1. *Relative humidity composite based on precipitation (RHCP) diagnostic*

Based on observational evidence of the strong coupling between convection and moisture (e.g., Bretherton *et al.* 2004; Peters and Neelin 2006; Holloway and Neelin 2009; Yasunaga and Mapes 2012), and also the great model sensitivity of MJO simulations to moisture–convection coupling (Zhu *et al.* 2009; Xavier *et al.* 2010; Hannah and Maloney 2011; Del Genio *et al.* 2012; Kim *et al.* 2012; Kim and Kang 2012), an RHCP metric was proposed for MJO model diagnoses (Kim *et al.* 2014). Specifically, the RHCP metric is formulated as the low-level (850–700 hPa) RH difference between the upper 10% precipitation percentile and the lower 20% precipitation percentile derived over the Indo-Pacific warm pool (60°E–180°, 15°S–15°N), measuring the amount of low-level RH increase required for a transition from weak to strong rain regimes, thus representing model convection sensitivity to environment moisture. A statistically robust relationship between the RHCP and model MJO performance has been illustrated in multi-model simulations (Kim *et al.* 2014; Jiang *et al.* 2015; Klingaman *et al.* 2015a; Ahn *et al.* 2017). For example, a correlation of about 0.56 was obtained between the RHCP metric and model MJO skill scores, denoted by the ratio of eastward versus westward power in planetary-scale, intraseasonal equatorial precipitation anomalies following Kim *et al.* (2009), based on 28 model simulations of Coupled Model Intercomparison Project Phase 5 (CMIP5) (Fig. 1a, Ahn *et al.* 2017).

3.2. *Normalized gross moist stability (NGMS)*

Under the moisture mode framework for the MJO (e.g., Raymond and Fuchs 2009; Sobel and Maloney 2012; Sobel and Maloney 2013; Adames and Kim 2016), recent analyses of the



(a) (b) (c)

Fig. 1. Scatter plots of model skill score for the MJO eastward propagation, denoted by the eastward versus westward power spectrum ratio of equatorial precipitation, and (a) RHCP, (b) NGMS, and the GEF metric averaged over 1–5 mm day^{-1} rainfall regime in 28 IPCC CMIP5 model simulations. See text for details of these metrics. Adapted from Ahn *et al.* (2017).

moist static energy (MSE) budget have yielded critical insights into key processes for the maintenance and propagation of the MJO (readers are referred to the chapter on the MJO moisture mode theory by Adames *et al.* in this collection for details). The results of the MSE budget analysis suggest that (i) radiative heating and surface fluxes serve as two primary energy sources in sustaining the MJO, while both horizontal and vertical MSE advections export energy in regions of MJO convection, and (ii) horizontal and vertical MSE advections help the MJO to propagate eastward by increasing/decreasing MSE to the west/east of the enhanced convection. A diagnostic metric of the NGMS (Neelin and Held 1987; Raymond *et al.* 2009), which is defined as MSE export through vertical and/or horizontal MSE advection per unit convective activity and measures the efficiency of the large-scale circulation in discharging MSE out of the atmospheric column, can be used as a metric for MJO instability. It is hypothesized that the NGMS should be small or negative in order to sustain strong MJO convection (Raymond and Fuchs 2009; Hannah and Maloney 2011; Sobel and Maloney 2012). By applying the NGMS diagnosis for six GCM simulations, Benedict *et al.* (2014) illustrated a robust relationship between the vertical component of the time-mean NGMS over the Indo-Pacific warm pool and MJO simulation skill. Statistically significant anti-correlations between the winter mean NGMS over the Indo-Pacific warm pool and MJO skill based on multi-model simulations are also obtained in Jiang *et al.* (2015) and Ahn *et al.* (2017). As shown in Fig. 1b, a correlation of about −0.47 was found between the vertical component of NGMS and model MJO skill scores in 28 model simulations (Ahn *et al.* 2017). Moreover, a strong anti-correlation (−0.9) between summer mean vertical NGMS and the amplitude of the summer MJO over the eastern Pacific was also noted in eight simulations based on three GCMs (Maloney *et al.* 2014).

3.3. *Greenhouse enhancement factor (GEF)*

Motivated by previous studies that feedback between the longwave radiation and clouds plays a critical role in destabilizing the MJO (e.g., Raymond 2001; Lin *et al.* 2004; Bony and Emanuel 2005; Jiang *et al.* 2011; Andersen and Kuang 2012, Sobel and Maloney 2012, 2013; Chikira 2014; Wolding and Maloney 2015; Wolding *et al.* 2016), a GEF, defined by the negative ratio of anomalous outgoing longwave radiation to anomalous precipitation, is used to represent the strength of longwave radiation and cloud interactions associated with the MJO (Kim *et al.* 2015). It was shown that a GEF metric, derived by the weighted average of GEF over a 1–5 mm day^{-1} precipitation anomaly regime, exhibits a statistically significant correlation to model MJO simulation skill across multi-model simulations (Fig. 1c, Kim *et al.* 2015; Ahn *et al.* 2017).

3.4. *Lower-tropospheric mean moisture pattern*

This diagnostic is motivated by the finding that the advection of column MSE or equivalently the lower-tropospheric moisture, particularly its horizontal component, plays a critical role in driving the eastward propagation of the winter MJO (e.g., Maloney 2009; Maloney *et al.* 2010; Andersen and Kuang, 2012; Kim *et al.*, 2014; Sobel *et al.* 2014 Chikira 2014; Adames and Wallace 2015; Arnold *et al.* 2015; Jiang 2017). Under this process, the spatial distribution of the winter mean lower-tropospheric moisture over the equatorial Indo-Pacific region (Fig. 2a) holds a key for moistening (drying) to the east (west) of the MJO convection through advection by MJO anomalous winds, thus promoting the eastward propagation of the winter MJO. The critical role of the mean lower-tropospheric moisture pattern for the eastward propagation of the MJO has been further confirmed by recent modeling studies based on multi-model simulations from the MJO Task Force/GEWEX GASS MJO model comparison project (Gonzalez and Jiang 2017; Jiang 2017). The model skill in representing the low-level (900–650 hPa) mean moisture pattern over the Maritime Continent region (red rectangle in Fig. 2a) exhibits a very high correlation (about 0.8) with model MJO propagation skill in about 25 climate model simulations (Fig. 2b; Gonzalez and Jiang 2017). The critical role of the mean lower-tropospheric moisture pattern for MJO prediction skill is also illustrated based on model hindcasts (e.g., Kim 2017; Lim *et al.* 2017).

It is noteworthy that a recent multi-model analysis for the boreal summer MJO over the Indian Ocean also suggests that, similar to the eastward propagation of the winter MJO, the summer mean lower-tropospheric moisture pattern is also critical for the northward propagation of the boreal summer MJO due to moistening/drying to the north/south of the boreal summer MJO by horizontal advection of mean moisture by the MJO circulation (Jiang *et al.* 2018). These results, therefore, suggest that the distinct propagation characteristics of the MJO between the boreal winter and summer are largely regulated by seasonal migration in the low-level mean moisture pattern (Jiang *et al.* 2018).

3.5. *Other metrics*

Other process-oriented metrics have also been explored and linked to MJO skill in multi-model simulations. A net moistening metric, depicted by a vertical profile of the moisture tendency as a function of rain rate, was found to be highly correlated to model MJO simulation skill (Klingaman *et al.* 2015a,b). It was hypothesized that the net moistening in the mid-troposphere under the moderate rain regimes (2–9 mm day^{-1}) is crucial for high-quality MJO simulations.

A multi-model analysis by Jiang *et al.* (2016) suggested that the convective moisture adjustment timescale in a model, defined by the ratio of intraseasonal perturbations of precipitable water and surface precipitation (e.g., Bretherton *et al.* 2004; Sobel and Maloney 2013), can be an excellent metric for MJO amplitude in model simulations. The convective moisture adjustment timescale depicts how rapidly precipitation must increase to remove excess column water vapor, or alternately the efficiency of surface precipitation generation per unit column water vapor anomaly. Rushley *et al.* (2018) found that the convective moisture adjustment timescale is commonly overestimated in

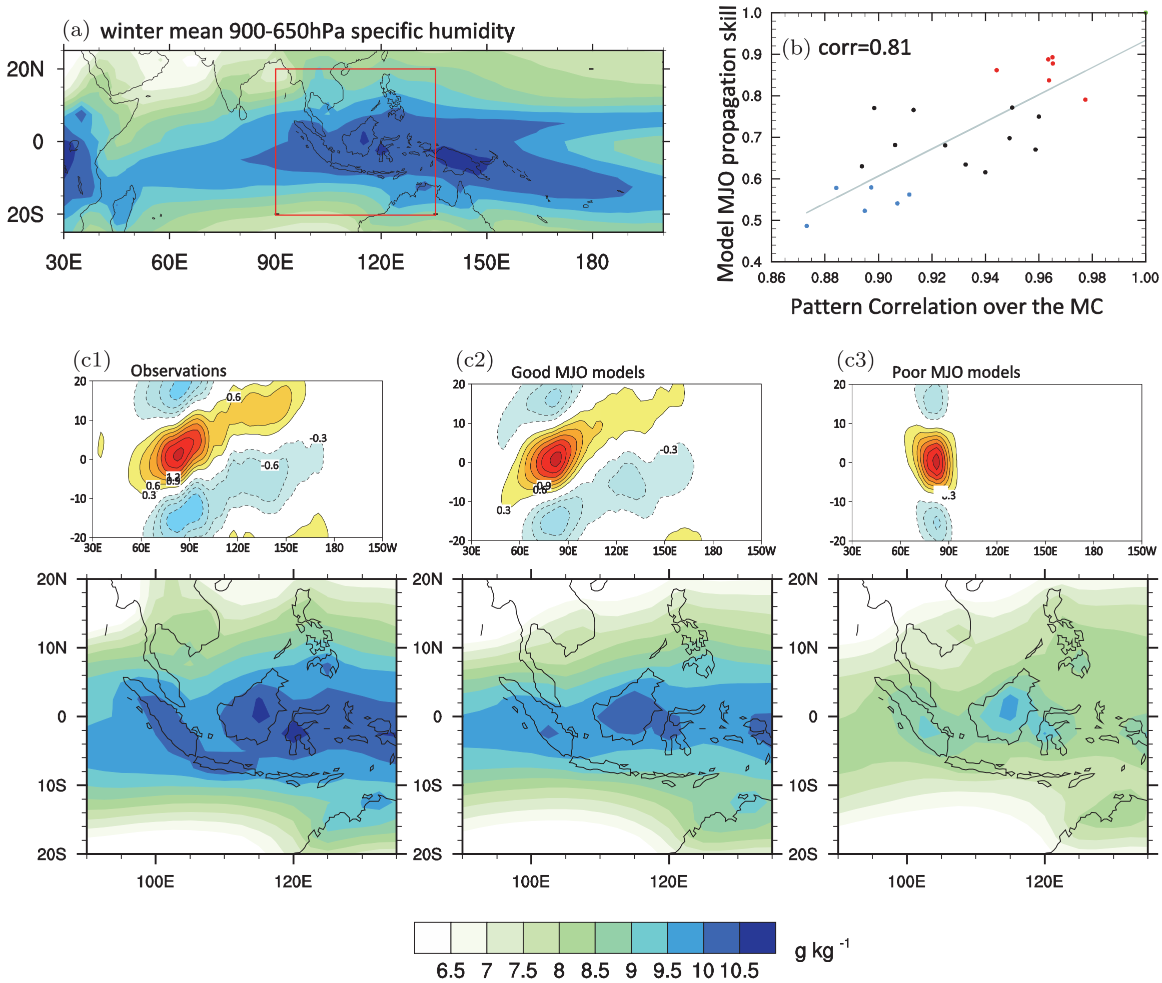


Fig. 2. (a) Winter mean 900–650 hPa specific humidity based on ERA-Interim; (b) scatter plot of model skill for eastward propagation of the MJO vs model skill of mean 900–650 hPa moisture over the Maritime Continent (MC; red rectangle in a) based on MJOTF/GASS model simulations. Red (blue) dots denote good (poor) MJO models. Lower panels: Time–longitude rainfall diagrams along the equator (10°S–10°N) and low-level (900–650 hPa) mean moisture over the MC in observations (c1), good (c2) vs poor (c3) MJO model composites. Hovmöller diagrams of rainfall anomalies associated with the MJO are derived based on lag-regression against an Indian Ocean box (75°–85°E; 5°S–5°N) for both observations and simulations (adapted from Jiang 2017 and Gonzalez and Jiang 2017).

GCMs. The key underlying physics regulating the convective moisture adjustment time scale needs to be further investigated (Jiang *et al.* 2016).

Additionally, analyses also suggested that the equatorial vertical-longitudinal distribution of diabatic heating, which depicts the multi-cloud structure of the MJO, could be used as a good metric for the MJO eastward propagation (e.g., Jiang *et al.* 2015; Wang *et al.* 2017). Meanwhile, the horizontal structure of boundary layer moisture convergence that provides moisture preconditioning in the lower troposphere to the east of the MJO convection center is also found to be highly correlated to MJO propagation across multi-model simulations (Wang and Lee 2017; Wang *et al.* 2018).

4. Summary and Discussion

Despite its tremendous influences on global weather and climate, the MJO remains poorly represented in the latest generation of GCMs. This grand challenge in modeling the MJO is largely due to model deficiencies in depicting cumulus processes and their interaction with the large-scale environment, as suggested by significant improvement of MJO simulations by replacing the cumulus parameterizations with explicit CRMs in these global GCMs, as well as other means of improving the representation of cumulus convection. While the CRM approach represents a future direction for model development, it is not practical in the near future for climate projection studies that need long-term integrations due to limitations in computing resources. Therefore, alternative affordable approaches to CRMs for improved depiction of subgrid cumulus processes in GCMs are worth investigating. In this chapter, an SMCM approach which provides a cheap way to represent interactions between multi-cloud structure within a GCM grid cell and large-scale conditions was briefly reviewed. Several recent implementations of an SMCM into GCMs suggest the great potential for the SMCM approach to improve simulations of the MJO and convectively coupled equatorial waves, although there is also room for refinement of the SMCM approach.

On the contrary, while improved MJO representation has been achieved in some GCMs including CRMs, an understanding of the essential model processes for realistic MJO simulations remains elusive. This gap has motivated recent efforts in the community on development of process-oriented metrics for the MJO as briefly introduced in this chapter. While statistically significant correlations between several process-oriented metrics and model skill for MJO propagation and/or amplitude are evident in multi-model simulations, uncertainties also exist in how these metrics are derived, as these correlations could be sensitive to changes in geographical domain, vertical levels, rain regimes, as well as observational and model datasets used for these metrics (e.g., Jiang *et al.* 2015; Kim *et al.* 2015; Ahn *et al.* 2017). Therefore, further investigations are needed to explore key model processes to discriminate good MJO models from poor ones, including further verification of these existing MJO metrics with independent model datasets. The upcoming CMIP6 will provide an excellent opportunity for continued efforts in process-oriented diagnoses of the MJO to obtain the knowledge necessary for improved MJO simulations in GCMs.

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