Linking Stochasticity of Convection to Large-Scale Vertical Velocity to Improve Indian Summer Monsoon Simulation in the NCAR CAM5

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ABSTRACT

The Plant–Craig (PC) stochastic convective parameterization scheme is modified by linking the stochastic generation of convective clouds to the change of large-scale vertical pressure velocity at 500 hPa with time so as to better account for the relationship between convection and the large-scale environment. Three experiments using the National Center for Atmospheric Research (NCAR) Community Atmosphere Model, version 5 (CAM5), are conducted: one with the default Zhang–McFarlane deterministic convective scheme, another with the original PC stochastic scheme, and a third with the modified PC stochastic scheme. Evaluation is focused on the simulation of the Indian summer monsoon (ISM), which is a long-standing challenge for all current global circulation models. Results show that the modified stochastic scheme better represents the annual cycle of the climatological mean rainfall over central India and the mean onset date of ISM compared to other simulations. Also, for the simulations of ISM intraseasonal variability for quasi-biweekly and 30–60-day modes, the modified stochastic parameterization produces more realistic propagation and magnitude, especially for the observed northeastward movement of the 30–60-day mode, for which the other two simulations show the propagation in the opposite direction. Causes are investigated through a moisture budget analysis. Compared to the other two simulations, the modified stochastic scheme with an appropriate representation of convection better represents the patterns and amplitudes of large-scale dynamical convergence and moisture advection and thus corrects the monsoon cycle associated with their covariation during the peaks and troughs of intraseasonal oscillation.

1. Introduction

Wang et al. (2016) implemented the Plant–Craig (PC) stochastic convective parameterization scheme (Plant and Craig 2008) into the National Center for Atmospheric Research (NCAR) Community Atmosphere Model, version 5 (CAM5), to account for the variability of subgrid-scale convection in the Zhang–McFarlane (ZM) deterministic deep-convection scheme (Zhang and McFarlane 1995). With the stochastic deep-convection scheme in CAM5, the simulated tropical and extratropical precipitation characteristics, including intensity, frequency, and variability, as well as other climate mean states, were improved (Wang and Zhang 2016; Wang et al. 2017). However, the simulated precipitation over central and north India and the Bay of Bengal was underestimated compared to observations, resulting in a degradation of the simulation of the Indian summer monsoon (ISM). The ISM from June to September (JJAS) has large spatial and temporal variability. Its conspicuous departure from normal precipitation (i.e., extreme events) can cause floods and droughts, severely impacting the ecological and human society systems of India (Chaudhari et al. 2010). Therefore, a
realistic simulation of ISM is an important metric for model fidelity, and it is highly desirable to alleviate this degradation after the PC stochastic deep-convection parameterization is introduced in CAM5.

As demonstrated in previous studies (Zhang 1994; Chung and Zhang 2004; Moncrieff et al. 2012; Waliser et al. 2012), a realistic simulation of the tropical climate system including the ISM in general circulation models (GCMs) is tightly associated with the accurate representation of subgrid-scale cloud and convection processes. To better represent the subgrid-scale cloud and convection processes, two approaches are developed recently. One is superparameterization (Grabowski and Smolarkiewicz 1999; Khairoutdinov and Randall 2001) in which a large number of cloud-resolving models (CRMs) are embedded in the GCM to explicitly resolve the subgrid-scale convection process. With this approach, some promising results are obtained in the simulation of the ISM (Krishnamurthy et al. 2014; Goswami et al. 2015). The other is the stochastic parameterization at a much lower computational cost, which is proposed as a modification to the convective deterministic parameterization schemes to introduce a stochastic component for representing fluctuations of subgrid-scale convection. This approach encompasses two categories of state-of-the-art stochastic convective parameterization schemes. One is a stochastic multicloud model (MCM) parameterization (Khoudier et al. 2010; Deng et al. 2015; Dorrestijn et al. 2013) using conditional Markov chain to simulate the stochastic transition of different cloud types. Goswami et al. (2017a,b) implemented this parameterization into the Climate Forecast System, version 2 (CFSv2), to improve the tropical synoptic and intraseasonal variability. Different from the MCM parameterization, Plant and Craig (2008) utilized the Gibbs canonical ensemble from statistical mechanics to develop a probability distribution function of cloud-base convective mass flux. As mentioned at the beginning of this section, we have implemented it into the NCAR CAM5, and noted some degradation of the simulation of ISM, although improvements in other aspects of precipitation simulation outweigh it.

In addition to their accurate representations, the interaction of subgrid-scale cloud and convection processes with the large-scale circulation is also important for the simulation of ISM and especially its intraseasonal variability (Jiang et al. 2011; Abhik et al. 2013). Several studies have pointed out that the absence or the improper characterization of their interactions in the GCMs could be responsible for the poor ISM simulation (e.g., Jiang et al. 2011; DeMott et al. 2011). The superparameterization potentially can solve this issue, but it is more computationally expensive. Therefore, an alternative way is the integration of their interactions into a stochastic framework. Recently, Gottwald et al. (2016) analyzed radar observations of convective area fraction (CAF) and large-scale vertical pressure velocity at 500 hPa $\omega_{500}$ averaged over about $200 \times 200$ km$^2$, a typical GCM grid size, in Darwin, Australia, and Kwajalein in the western Pacific, and found that large CAF occurred frequently under strong upward $\omega_{500}$. A possible physical explanation for this observed relationship is that under strong large-scale forcing, convection is more organized and thus cloud sizes are larger. They considered this relationship using two stochastic approaches respectively (one is instantaneous conditional random variables and the other is conditional Markov chain) and adequately reproduced the statistics of the observed CAF. Therefore, as an extension, the MCM parameterization (Peters et al. 2013; Dorrestijn et al. 2015) linking the transition probabilities among different cloud categories to large-scale vertical velocity moderately improved the synoptic and intraseasonal variability of the ISM in CFSv2 (Goswami et al. 2017b). Motivated by these studies and because of the absence of the impact of large-scale circulation in the PC stochastic convective parameterization, we modify the original PC scheme to consider the relation between the stochastic generation of convective clouds and large-scale atmospheric circulation. Along with the modified PC parameterization, the performance of the original PC scheme as well as the default ZM scheme on the simulation of the ISM is analyzed in this study.

The remainder of the paper is organized as follows: CAM5, model experiments, and evaluation data are described in section 2. Section 3 provides analysis results including climate mean states, the basic precipitation characteristics of ISM and its intraseasonal variation, and moisture–precipitation coupling in the variation. Conclusions are presented in section 4.

2. CAM5, model experiments, and evaluation data
   a. CAM5 with the default ZM deterministic scheme

The NCAR CAM5.3 is used in this study. The default deep-convection scheme is the ZM deterministic scheme (Zhang and McFarlane 1995), with an update from Neale et al. (2008) to consider dilute convective available potential energy (CAPE). Same as other deterministic convection schemes, the ZM scheme describes the ensemble mean effects of subgrid-scale convective clouds and thus the fluctuations associated with individual clouds are averaged out. Besides the deep-convection parameterization, the shallow convection scheme is based on Park and Bretherton (2009) and moist turbulence is parameterized using Bretherton and Park (2009). The cloud microphysics scheme following Morrison and Gettelman (2008) and Gettelman et al. (2008) and the cloud microphysics scheme following Park et al. (2014) are used to parameterize
clouds. The radiation module is from the Rapid Radiative Transfer Model (RRTM; Iacono et al. 2008). All of our model experiments in this study are conducted with CAM5.3. One of them is the control (CTL) simulation using the default ZM deterministic convection parameterization, and the others are run with the following modifications to the deep-convection parameterization.

\section*{b. The PC stochastic scheme}

In the PC scheme, the stochastic generation of convective clouds follows the Poisson distribution for the probability of occurrence of a cloud with a given cloud mass flux. The implementation of the PC stochastic deep-convection parameterization into the CAM5 in Wang et al. (2016) to couple with the ZM deterministic convection parameterization is briefly summarized here. The probability of triggering one cloud is given by

\[ P_{dn}(n=1) = \frac{\langle N \rangle}{\langle m \rangle} e^{-m/m_d} dm, \]  

(1)

where \( d\bar{m}(m) \) denotes the average number of clouds with mass flux between \( m \) and \( m + dm \); \( \langle m \rangle \), with a value of \( 1 \times 10^7 \text{kg s}^{-1} \), is the ensemble mean mass flux of a cloud; and \( \langle N \rangle = \langle M \rangle / \langle m \rangle \), where \( \langle M \rangle \) is ensemble mean total cloud mass flux given by the closure in the ZM deterministic parameterization) is the ensemble mean number of convective clouds in a given GCM grid box. The entire \( m \) range is divided into 100-bin intervals with varying bin sizes. In the actual probability calculation in Eq. (1), \( \langle N \rangle \) is absorbed into \( dm \) [i.e., \( dm' = \langle N \rangle dm \), and \( dm' \) is fixed as a constant, see Wang et al. (2016) for details], so that the probability of triggering one cloud is an exponential function of \( m \). Convective clouds with smaller (larger) \( m \) values have larger (smaller) probabilities of occurrence. For each mass flux bin, whether to launch a cloud is determined by comparing the probability from Eq. (1) with a random number at a given interval at each following time step according to the following conditions,

\[
\begin{align*}
\text{launch}_i &= \text{true.}, \quad \text{if } P_{dn}(m_i) > r_i \\
\text{launch}_i &= \text{false.}, \quad \text{if } P_{dn}(m_i) \leq r_i.
\end{align*}
\]  

(2)

Here subscript \( i \) indicates the \( i \)th bin interval, \( m_i \) is the mass flux, and \( r_i \) is the random number generated in this interval. Here, \( \text{launch}_i = \text{true.} \) (\( \text{launch}_i = \text{false.} \)) indicates that the cloud in the \( i \)th interval is (is not) launched. Thus, a small (large) random number facilitates (suppresses) the initiation of the convective cloud. The random numbers in all bin intervals at each grid point are updated once a day (at the beginning time step of each day, i.e., 0000 UTC) to roughly account for the lifetime of convective systems. Summing all successfully launched convective clouds of different mass fluxes (or equivalently different cloud sizes) in a given GCM grid box gives the actual total mass flux \( M \) that departs from its ensemble mean mass flux \( \langle M \rangle \) and is independent of large-scale atmospheric circulation states (e.g., vertical velocity). The CAM5 simulation using the PC stochastic parameterization is referred to as PC.

\section*{c. Linking stochastic generation of convection to large-scale vertical velocity}

Motivated by the recent work of Gottwald et al. (2016) and Goswami et al. (2017a,b), which relates subgrid-scale CAF to large-scale \( \omega_{500} \) (negative upward) through the conditional Markov chain, we modify the PC stochastic scheme by incorporating the information of large-scale \( \omega_{500} \) in the generation of convective clouds. We will qualitatively allow for a higher probability of occurrence for larger convective cloud-base mass flux (or equivalently larger convective clouds) under stronger large-scale upward \( \omega_{500} \), and a higher probability of occurrence for smaller convective cloud-base mass flux (or equivalently smaller convective clouds) under weaker large-scale upward \( \omega_{500} \).

From Eq. (2), the random numbers stochastically affect the initiation of convective clouds of different sizes. Therefore, by adjusting the random numbers, the logical switch represented by Eq. (2) can be controlled to aid the launch of convective clouds of certain sizes associated with a given large-scale upward \( \omega_{500} \). Modifications are made as follows. After generating all random numbers in all mass flux intervals at each grid point at the beginning time step of each day, we make an adjustment to a random number at a given interval at each following time step according to the following conditions,

\[
\begin{align*}
\text{launch}_{t-1} &= \text{false.}, \quad \text{if } \omega_{500,t-1} < \omega_{500,t} \quad \text{and} \quad r_i = \min(r_i, r_{t,i}) \\
\text{launch}_{t-1} &= \text{true.}, \quad \text{if } \omega_{500,t-1} > \omega_{500,t} \quad \text{and} \quad r_i = \max(r_i, r_{t,i}).
\end{align*}
\]

(3)

Otherwise, the random number is unchanged. Here subscript \( t \) denotes the current model time step and \( t - 1 \) denotes the previous time step; \( r_{t,i} \), \( r_{t-1,i} \) is the newly generated random number at the \( j \)th trial (e.g., \( r_{t,1} \) for the first trial) in the \( i \)th bin interval to be used for potential replacement of \( r_i \) (i.e., adjusting the random number for the purpose of facilitating or suppressing the generation of that convective cloud in the \( i \)th bin interval). Since the
newly generated random number may or may not satisfy the launch condition Eq. (3), we will keep trying until one that does satisfy the condition is found or until the number of trials reaches the preset limit, which is set to 20. Whether a smaller or larger random number relative to the value at the previous time step is regenerates for replacement to facilitate or suppress the generation of the convective cloud is based on the large-scale upward $\omega_{500}$ at the current step relative to $\omega_{500}$ at the previous time step. If a stronger (weaker) upward $\omega_{500}$ (negative upward) occurs at the current time step than at the previous time step and at the same time the convective cloud in the $i$th bin interval was not (was) launched at the previous time step, a smaller (larger) random number will be used at the current time step to replace the original one in Eq. (2) to determine if convection should be launched. In other words, if large-scale upward motion $\omega_{500}$ intensifies (weakens) from the previous time step to the current time step, the suppressed (initiated) convective cloud at the previous time step will have an opportunity to be (not to be) launched at the current time step by using a smaller (larger) random number to compare with its triggering probability $p_{\text{init}}(\omega_500(n = 1).$ For the selection of the intervals in which the serial adjustments are made with time, it follows a descending (ascending) order with stronger (weaker) upward $\omega_{500}$. With this, the convective clouds with large (small) cloud-base mass flux compared to those with moderate cloud-base mass flux will be initiated (suppressed) first, not only for effectively further suppressing too light but too frequent precipitation but also for enhancing intense precipitation (Wang et al. 2016). Thus, as $\omega_{500}$ continuously evolves with time during each day (e.g., Rasp et al. 2018), this adjustment is increasingly accumulated to mimic the evolution of convective systems. For instance, if upward $\omega_{500}$ continuously increases first, an increasing number of large convective clouds (i.e., more organized) will be generated because of the smaller random numbers used in comparison, resulting in the increase of CAF. Afterward, if the upward $\omega_{500}$ becomes weaker, small convective clouds associated with the large random numbers perish first to initiate the decrease of CAF.

Equation (3) considers the change of $\omega_{500}$ with time when changing the random number from the previous time step to the current time step. This, in effect, relates the random number to $\omega_{500}$. Since the random number dictates the cloud mass flux, convective mass flux (or equivalently CAF) is related to $\omega_{500}$ through the random number population. In this regard, the modification is supported by the work of Gottwald et al. (2016). To illustrate the impact of a link with $\omega_{500}$ on the cloud size population explicitly, Fig. 1 shows large-sample statistics calculated offline of the occurrence frequency of clouds of different sizes from the PC and the modified PC (referred to as PCW) schemes. Ten days of hourly $\omega_{500}$ output at a grid point (16°N, 77.5°E) over India from CAM5 are used repeatedly in Eq. (3) to generate the random numbers in each cloud mass flux bin and launch clouds according to Eqs. (1) and (2). The maximum number of trials at each time interval (60 min, here) of the data is set to 20 and all random numbers are updated at 0000 UTC each day. Note that the offline calculation in Fig. 1 shows the impact of an $\omega_{500}$ series on the shape of the cloud size distribution only. In the actual model, other factors such as the large-scale atmospheric states could affect the triggering of the cloud population as well. Compared with the PC scheme, the changes in the PCW scheme mainly occur in the occurrence probabilities of small and large clouds. This is because the targeted clouds associated with random number adjustments within a day follow a descending (ascending) order with stronger (weaker) upward $\omega_{500}$. The increase of the occurrence probability of large clouds, to some extent, can account for the strongly organized systems associated with persistent large-scale vertical motion that are likely not in equilibrium. Since clouds in organized convective systems are often not separated (i.e., clustered), the occurrence frequency of large clouds in the PCW scheme is similar to the study in Rasp et al. (2018). They evaluated the applicability of the Craig and Cohen (2006, hereinafter CC06) theory in real-weather case studies of nonequilibrium summertime convection over land. They found that the assumption of nonseparated cloud mass flux results in a higher occurrence probability in large clouds.

In the PCW scheme, there are two tunable parameters. One is the reset time of each day (the default reset time of each day is 0000 UTC) and the other is the number of trials for random number generation. We tested different reset times (0600, 1200, and 1800 UTC),
and the results are not sensitive to the reset time (figure not shown). For the number of trials, a smaller limit of the number of trials makes the convective mass flux less coupled with $q_{500}$, and a larger limit makes it more coupled with $q_{500}$. More (fewer) trials increases (decreases) the occurrence probability of large clouds. In contrast, the change in small clouds is less sensitive because of their high occurrence frequency relative to the number of trials (figure not shown). A limit of 20 trials as the default is optimal in simulating the frequency distribution of precipitation rates when compared to TRMM observations. Additionally, it should be noted that the impact of the length of time step on Eq. (3) should be considered if applying the modified PC scheme to other models or other resolutions of the same model. A smaller time step means a stronger coupling with $q_{500}$ if the number of trials is unchanged. In this case, the number of trials, as a tunable parameter, may need to be reduced to avoid too strong a coupling with $q_{500}$.

d. Experiment setup and evaluation data

Three simulations (i.e., CTL, PC, and PCW) are conducted for 16 years from 1990 to 2005. With 1-yr spinup, the last 15 years (1991–2005) are used for analysis. The simulation setup is the same as used in Wang et al. (2016): atmosphere only with prescribed sea surface temperatures and sea ice extent at a horizontal resolution of $1.9^\circ \times 2.5^\circ$ and 30 vertical levels.

The observational data for evaluation of the ISM is precipitation from the Tropical Rainfall Measurement Mission (TRMM) 3B42 daily product (Huffman et al. 2007) and Global Precipitation Climatology Project (GPCP), version 1.2, 1° daily (1DD) observations (Huffman et al. 2012). The Modern-Era Retrospective Analysis for Research and Applications (MERRA) reanalysis data (Rienecker et al. 2011) are used in section 3b for diagnosis of connections between precipitation and large-scale moisture advection and dynamical convergence.

3. Results

a. Model simulations of ISM

While relating the stochastic generation of convective clouds to large-scale $q_{500}$ is physically sound, from model performance point of view, however, we require that the simulated climate mean states be at least comparable to those in Wang and Zhang (2016) and Wang et al. (2017). With this in mind, we show a summary of various statistics from the three experiments (CTL, PC, and PCW) in Fig. 2 using a Taylor diagram (Taylor 2001). These evaluation metrics are based on observations and reanalysis data, which are the GPCP monthly product (version 2.1; Adler et al. 2003; Huffman et al. 2009) for precipitation, the Clouds and the Earth’s Radiant Energy System (CERES) Energy Balanced and Filled (EBAF; Loeb et al. 2009) for shortwave (SW) and longwave (LW) cloud radiative forcing, the European Remote Sensing Satellites (ERS) scatterometer (Bentamy et al. 1999) for surface wind stress, the Willmott–Matsuura (labeled Willmott in Fig. 2; Willmott and Matsuura 1995) dataset for land surface air temperature, and the ECMWF interim reanalysis (ERAI; Simmons et al. 2006) for sea level pressure, zonal wind, relative humidity, and temperature. Overall, all simulated statistics between the PCW and PC simulations are comparable, both outperforming the CTL run-in simulations of shortwave and longwave cloud forcing, land rainfall, and Pacific surface stress. The degradation of ocean rainfall in both PC and PCW simulations compared to the CTL simulation is mainly due to too much precipitation over the intertropical convergence zone (ITCZ), South Pacific convergence zone (SPCZ), and equatorial Indian Ocean (see Fig. 3) where large-scale precipitation and convective precipitation from shallow convection are increased (Wang and Zhang 2016).

Figure 3 shows the total precipitation from the CTL run, the PC run, the PCW run, and the TRMM observations for JJAS over the tropics, with zoom-in for the ISM region on the right. Overall, except over the ISM region and the equatorial Indian Ocean, the precipitation climatology (including spatial distribution and amount) in the tropics simulated by the PCW run is similar to that in the PC run. Over the equatorial Indian Ocean, the PCW run reduces the overestimated bias in the PC run. In the ISM region, the simulated precipitation in PCW shows a better agreement with the TRMM observations compared to other simulations. The CTL run dramatically overestimates precipitation over central and northern India, the west coast, and the Bay of Bengal (Fig. 3f). The use of the PC scheme reduces this overestimation by too much, resulting in underestimated precipitation over the Bay of Bengal (Fig. 3g). The PCW run, with the highest spatial correlation (0.61) and the smallest spatial root-mean-square error (RMSE) ($2.89 \text{mm day}^{-1}$) with respect to the TRMM observations, alleviates the excessive reduction of precipitation in the PC run (Fig. 3h), leading to a closer agreement with the observations.

In terms of the annual cycle of rainfall over central India (Fig. 4a), there is also a clear improvement in the PCW run in comparison with the CTL and PC experiments. The CTL run simulates an earlier onset month (May) and a later withdrawal month (October) of the ISM, thus producing a prolonged monsoon season. The maximum monsoonal precipitation during July and
August is also overestimated. On the other hand, while the PC run simulates the onset and withdrawal months well, the rainfall amount during the peak monsoon period of July and August is underestimated. By relating the probability of occurrence of cloud mass flux to 500-hPa large-scale vertical velocity, the PCW run not only produces the maximum monsoonal precipitation much more comparable to observations during July and August (although somewhat overestimated in August), but also correctly captures the onset and withdrawal months of the ISM. Similar to Fig. 3a in Wang et al. (2016), Fig. 4b shows the frequency distribution of precipitation rates from all grid points over central India for JJAS in observation and simulations. In comparison with observations, CTL simulates too-frequent light precipitation but undersimulates the frequency of intense precipitation. The PC run significantly reduces these biases, which, as discussed in Wang et al. (2016), can be attributed to the use of the Poisson process to launch convective clouds of different mass flux. The PCW run further improves the frequency distribution of precipitation rates larger than 30 mm day$^{-1}$. This is because an increase in upward motion has a higher probability of producing stronger convection in the PCW run (Fig. 1).

The onset time of ISM is an important metric for monsoon simulation. It is often measured by a method proposed by Liebmann and Marengo (2001) and Bombardi and Carvalho (2009) using the following equation:

$$S(t) = \sum_{t=1}^{i} [R(t') - R_m],$$

where $R$ is the daily precipitation, $R_m$ is the annual mean of precipitation and the summation starts from day 1 of the calendar year (note that the result is not sensitive to a specific start date in the dry season), and $S$ is the cumulative precipitation anomaly calculated for...
each GCM grid point. At the beginning, $S$ is negative. When precipitation occurs frequently, $S$ starts to increase. A 1–2–1 filter is applied to the $S$ curve so that its time derivative $\frac{dS(t)}{dt}$ is not too noisy. The date when $\frac{dS(t)}{dt}$ changes sign from negative to positive (i.e., precipitation is above the annual mean) is referred to as the onset date of the rainy season. Similarly, when the computation of $S$ starts from the wet season, the date when $\frac{dS(t)}{dt}$ changes sign from positive to negative is referred to as the withdrawal date of the rainy season.

Figure 5 shows the progression of the onset of ISM in each simulation and TRMM observations in day-of-year (DOY). In observations, except the latest ISM onset (DOY 165) on the leeward side of the Western Ghats, there is a northwestward progression of the ISM onset [i.e., from southern (DOY 135) to central India (DOY 145) and to northwestern India (DOY 155)], which is consistent with previous studies (e.g., Joseph et al. 1994; Fasullo and Webster 2002; Bombardi et al. 2015). Although the CTL run reproduces this propagation, the
onset dates are earlier than those in observations, especially over central India (10–15 days in advance). For the PC run, although it improves the onset dates over central India, it fails to reproduce the observed propagation, showing a northward propagation. In comparison to the CTL and PC simulations, the PCW simulation shows very close monsoon onset dates to the observed ones over central India (although 5 days late over northwestern India) and a more realistic northwestward progression.

The above results demonstrate clear improvements to the simulations of the characteristics of ISM in the PCW run. The monsoon oscillations including high- (quasi biweekly) and low-frequency (30–60 day) modes are also prominent features of ISM (Goswami et al. 2013, 2014; Maharana and Dimri 2016; Umakanth et al. 2016). Their simulations are evaluated next. Figure 6 shows the propagation features of the quasi-biweekly mode (10–20-day bandpass-filtered rainfall anomalies) obtained by regressing the filtered precipitation anomalies onto the corresponding central India precipitation index (CIPI), which is defined as a reference precipitation time series generated by averaging the filtered precipitation anomalies over central India (18°–28°N, 73°–82°E) (Goswami et al. 2015). In the longitude–time Hovmöller plot of precipitation averaged over 10°–20°N, the TRMM observations show a westward propagation with no obvious intensification over the longitudes of the Indian subcontinent. All simulations reproduce the observed westward movement; however, CTL and PC exhibit a much stronger amplitude west of 90°E than observations. This is alleviated to some extent in the PCW simulation. For the latitude–time plot (Figs. 6e–h), observations show a northward propagation with a maximum amplitude centered over 18°–20°N. All three experiments capture this observed movement as well, but their simulated maximum amplitudes differ considerably. The CTL run not only overestimates the

![Figure 5](https://example.com/fig5.png)

**Fig. 5.** Mean onset dates of the ISM (DOY) for (a) TRMM, (b) CTL, (c) PC, and (d) PCW.
maximum amplitude over 18°–20°N, but also has a second maximum over the equator. Although the PC run does not produce this maximum over the equator, the simulated maximum amplitude over 18°–20°N is still too large. In comparison, the PCW run not only eliminates the fictitious maxima south of the equator, but also has a similar maximum amplitude to that in observations over 18°–20°N. In terms of northward propagation speed, all simulations show too-fast propagation (the simulation in the PCW run is degraded from the PC run, though).

The propagation features of the 30–60-day (intra-seasonal) mode (30–90-day bandpass-filtered rainfall anomalies) are shown in Fig. 7. In observations, there is a clear northeastward propagation of the intra-seasonal precipitation signals (Figs. 7a,e). On the other hand, both CTL and PC runs exhibit northwestward propagation (Figs. 7b,c). When the probability of occurrence of convective mass flux is linked to $w_{500}$ in the PCW run, it shows an eastward propagation east of 105°E and west of 75°E as in observations, although there is still a westward propagation between 75° and 105°E. This feature actually outperforms the simulation by the superparameterization in the CFSv2 (Goswami et al. 2015), signifying the difficulty in improving the intraseasonal variability of ISM. For the northward propagation component, observations show maximum amplitude of precipitation anomalies at around 20°N (Fig. 7e). This is realistically reproduced by all three simulations.

b. Moisture–precipitation coupling in ISM intra-seasonal variation

From the above analyses, linking the stochastic generation of convective clouds to large-scale $w_{500}$ in the PCW run results in improvements in precipitation characteristics including the mean state and variability. To understand why the PCW run leads to these changes in precipitation, we will analyze the moisture–precipitation coupling during the intraseasonal oscillation (ISO) following the approach of Wang et al. (2015). First, for easy comparison with Wang et al. (2015), the GPCP daily precipitation data instead of the TRMM observations are used to identify the phases of the ISO in observations. The observed daily precipitation for the period of 1997–2004 spatially averaged over the Indian subcontinent (10°–25°N, 70°–90°E) is bandpass filtered for the periods of 10–90 days to retain both high- (quasi biweekly) and low-frequency (30–60 day) modes of oscillation of the ISM. To be consistent with Wang et al. (2015), the ISO peaks (troughs) are chosen to be the dates on which the
filtered precipitation maxima (minima) exceed one standard deviation from the mean. Figure 8 shows the original daily mean rainfall time series before the filter is applied over the Indian subcontinent during the ISM (from May to September) with the peak and trough dates marked by red and blue dots. The time period from the ISO peak to the ISO trough indicates the decaying phase while the opposite transition indicates the developing phase. With the same method, the respective ISO peak and trough dates in the three simulations and the MERRA reanalysis data (at 1.25° resolution) for the same period are identified as well. Following Wang et al. (2015), anomalies of all variables used in the following analyses are obtained by subtracting the seasonal cycles (i.e., 31-day window mean) from their absolute values.

Figure 9 shows the distribution of precipitation anomalies for GPCP, MERRA, and the three simulations on the ISO peak and trough dates, respectively. In the GPCP observations, there are positive precipitation anomalies over the Indian subcontinent and negative precipitation anomalies over the Indian Ocean during ISO peaks, while the patterns are opposite during ISO
troughs. In comparison with the GPCP observations, the overall patterns of anomalous precipitation during the ISO peaks and troughs in the MERRA reanalysis data agree well, but the amplitude of precipitation anomalies is about 30% smaller. For model simulations, all runs successfully reproduce the observed distribution of precipitation anomalies in the ISO peaks and troughs. Overall, the simulated magnitudes of anomalous precipitation during both peak and trough phases in the three simulations over the Indian subcontinent also compare well with those in observations. However, the magnitudes of anomalous precipitation over the Indian Ocean in the three simulations differ. The CTL run significantly underestimates the precipitation anomalies. In the both PC and PCW runs, the precipitation anomalies are increased and are comparable to those in the GPCP observations.

Next, we perform a moisture budget analysis to examine the moisture–precipitation coupling in the three simulations. The atmospheric water vapor budget equation has been widely used to diagnose changes in precipitation (Seager et al. 2010; Yin et al. 2013; Wang et al. 2015; Gao et al. 2017). It can be expressed as follows:

$$\frac{\partial W}{\partial t} = - \nabla \cdot (W \mathbf{v}) - P + E. \tag{5}$$

The first term on the right-hand side can be further written as

$$- \nabla \cdot (W \mathbf{v}) = (- W \nabla \cdot \mathbf{v}) + (- \mathbf{v} \cdot \nabla W) = Q_{\text{cnvg}} + Q_{\text{advt}}. \tag{6}$$

Here $P$ is precipitation, $E$ is evaporation, $W$ is column-integrated precipitable water, given by $W = \int_{p_{\text{surf}}}^{p_{\text{top}}} q \, dp / g$, where $q$ is specific humidity, $p$ is pressure, and $g$ is gravitational acceleration. The variable $\mathbf{v}$ is the total horizontal flux of water vapor in an atmospheric column normalized by column-integrated water vapor, having the form of $\mathbf{v} = W^{-1} \int_{p_{\text{surf}}}^{p_{\text{top}}} (u q) \, dp / g$, where $u$ is the horizontal wind vector. From the Eqs. (5) and (6), precipitation minus evaporation ($P - E$) and the atmospheric total water vapor storage ($dW / dt$) are determined by dynamical convergence $Q_{\text{cnvg}} (- W \nabla \cdot \mathbf{v})$, a measure of atmospheric circulation, and moisture advection $Q_{\text{advt}} (- \mathbf{v} \cdot \nabla W)$, a measure of horizontal moisture inhomogeneity. In the following analyses, $Q_{\text{cnvg}}$ and $Q_{\text{advt}}$ calculated from MERRA reanalysis will be used as a pair of large-scale dynamical conditions to investigate the moisture–precipitation coupling and compare with the model simulations.

The large-scale dynamical contributions from convergence and advection ($Q_{\text{cnvg}}, Q_{\text{advt}}$) in the MERRA reanalysis data and simulations during the ISO peaks and troughs are shown in Figs. 10 and 11, respectively. The sum of anomalous $Q_{\text{cnvg}}$ and $Q_{\text{advt}}$ corresponds well with most of the anomalous precipitation variations during the ISO peaks and troughs in Fig. 9. In both the MERRA reanalysis and model simulations, $Q_{\text{cnvg}}$ is a dominant term in regulating the wet/dry spells of the ISM over much of the Indian subcontinent (Wang et al. 2015). However, $Q_{\text{advt}}$ dominates the anomalous precipitation in the southwest coast by the Arabian Sea on the windward side of the Western Ghats. This is because over the Western Ghats, as a result of elevated topography, the column-integrated water vapor is much smaller than that upstream, creating a strong gradient of column-integrated water vapor, thereby resulting in large $Q_{\text{advt}}$ there. Compared with the MERRA reanalysis data, the three simulations all have stronger
$Q_{\text{cnvg}}$ anomalies over the Indian subcontinent, which thereby result in a better agreement with the GPCP observations in the magnitude of anomalous precipitation (Fig. 9). However, none of the experiments simulate the sharp changes of $Q_{\text{cnvg}}$ anomalies from the windward to the leeward sides of the Western Ghats and the dominant role of $Q_{\text{advt}}$ anomalies over the southwest coast by the Arabian Sea seen in the MERRA reanalysis data. This is likely due to the coarse resolution ($\sim 2^\circ$) of the model that cannot resolve the Western Ghats accurately. Over the Indian Ocean, the weak $Q_{\text{cnvg}}$ anomalies in the CTL run and the spurious $Q_{\text{cnvg}}$ anomalies in the PC run cause their respective biases of precipitation anomalies while the PCW run has similar patterns to those in the MERRA reanalysis data but with stronger amplitudes. For the simulation of $Q_{\text{advt}}$ anomalies, the overall patterns in the three simulations are comparable to those in the MERRA reanalysis data, but with weaker variations on the windward and leeward sides of the Western Ghats.

To further investigate the gradual transition of precipitation and large-scale dynamical states between the ISM active and break phases, Fig. 12 shows the latitude–time Hovmöller diagrams of composite anomalies of precipitation and ($Q_{\text{cnvg}}, Q_{\text{advt}}$) averaged over 70°–90°E, in which day 0 indicates the ISO peaks. In GPCP observations, approximately 10 days before the ISO peaks, there is a well-organized and positive anomaly starting over the Indian Ocean (10°S–5°N). Then it propagates northward at a rate of about 1.5° day$^{-1}$ in latitude, peaking over the Indian subcontinent (10°–25°N) at day 0 (ISO peaks) associated with a negative rainfall anomaly occurring over the Indian Ocean and then propagating at the same rate before the ISO troughs.
Again, the MERRA reanalysis data simulate a similar gradual transition of precipitation to that in the GPCP observations but with smaller magnitudes. All three simulations reproduce the features north of 5°N but have unrealistic gradual transitions over the Indian Ocean, although the negative rainfall anomaly over the Indian Ocean at day 0 is reproduced in the PCW run. In connection with the large-scale dynamical states in the MERRA reanalysis data, both $Q_{cnvg}$ and $Q_{advt}$ resemble the northward propagation of anomalous precipitation. Again, the three simulations fail to reproduce this continuous northward propagation of the large-scale dynamical features from the Indian Ocean to central India. In the MERRA reanalysis data, we can see that $Q_{cnvg}$, which is larger than $Q_{advt}$, dominates the total variation of precipitation throughout the transition. Nonetheless, positive anomalies of $Q_{advt}$, which lead positive anomalies of $Q_{cnvg}$ by 4–6 days, play an important role in favoring the development toward ISO peaks because moisture advection, playing a role in destabilizing the atmosphere, can precondition the environment for the development of deep convection (Kuo 1974; Fu et al. 2006; Yang et al. 2008; Wong et al. 2011). During this process, a typical transition of shallow convective clouds to deep convective clouds occurs (Kiladis et al. 2005; Wang et al. 2015). Similarly, negative anomalies of $Q_{advt}$ lead negative $Q_{cnvg}$ anomalies by 6–8 days, which favors the decaying phase toward ISO troughs. As suggested in several studies (e.g., Jiang et al. 2004; Del Genio et al. 2012; Wang et al. 2015), these characteristics of the variations of $Q_{cnvg}$ and $Q_{advt}$ reflect the moisture–convection feedback mechanism that implies the moistening associated with convection is critical to initiating and maintaining the ISO. Therefore, an accurate representation of the covariation of $Q_{cnvg}$ and $Q_{advt}$ anomalies is important to the simulation of ISM in GCMs. Consistent with the
MERRA reanalysis data, all the simulations also show the dominant role of $Q_{cnvg}$ variation in determining the total variations of precipitation throughout the transitions. However, in the CTL and PC runs, $Q_{advt}$ anomalies do not correspond well to those of $Q_{cnvg}$ as well as that in the MERRA reanalysis data, not exhibiting positive (negative) anomalies of $Q_{advt}$ leading positive (negative) anomalies of $Q_{cnvg}$ in concert. By linking the stochastic generation of convective clouds to $v_{500}$, the PCW run successfully simulates the covariation patterns of $Q_{cnvg}$ and $Q_{advt}$ anomalies, implying a potential to represent the development of deep convective clouds from shallow convective clouds (Wang et al. 2015). Besides, in contrast to the CTL and PC simulations, a negative $Q_{cnvg}$ anomaly over the Indian Ocean at day 0 in the PCW run agrees well with that in the MERRA reanalysis data.

Figure 13 further demonstrates the orbits of ($Q_{cnvg}$, $Q_{advt}$) anomalies averaged over the Indian subcontinent (10°–25°N, 70°–90°E) and the Indian Ocean (10°S–5°N, 70°–90°E) tracked by these two variables in the MERRA reanalysis data and simulations. In Fig. 13, the progression around the origin indicates monsoon evolution, in which the distances from the origin measures the amplitude of monsoon disturbance and the direction relative to the sign of $Q_{advt}$ measures monsoon phases. Therefore, the preconditioning (blue dots) that favors the development of deep convection is associated with negative $Q_{cnvg}$ anomalies and positive $Q_{advt}$ anomalies, occurring in the second quadrant. In contrast, the decaying phase after ISO peaks (green dots) with positive $Q_{cnvg}$ anomalies and negative $Q_{advt}$ anomalies is located in the fourth quadrant. Over the Indian subcontinent, the progression around the origin is clockwise in the MERRA reanalysis data while the CTL and PC runs show a counterclockwise progression. The unrealistic representations of progression around the origin in the CTL and PC runs indicate that the preconditioning by moisture advection to moisten the lower atmosphere before ISO peaks and the decaying phase with negative moisture advection to dry the atmosphere after ISO peaks are missing. In addition, the simulated maximum $Q_{advt}$ anomalies in the CTL and PC runs are more than 50% smaller than those in the MERRA reanalysis data, indicating weaker $Q_{advt}$ anomalies in these two simulations. Incorporating a link between the stochastic generation of convective clouds and large-scale $v_{500}$ in the PCW run correctly simulates the clockwise progression and increases $Q_{advt}$ variation to some extent (although still smaller than that in the MERRA reanalysis data). Over the Indian Ocean, the progression around the origin is clockwise as well in the MERRA reanalysis data but with a smaller and less coherent orbit, implying a less evident cycle of the monsoon. This is because we used indices over the Indian subcontinent to identify the
monsoon cycle over the Indian Ocean. Had we used the indices over the Indian Ocean, the orbit would have been conspicuous as well (Wang et al. 2015). Different from the results over the Indian subcontinent, both CTL and PC runs, like the PCW run, correctly reproduce the progression of the monsoon cycle over the Indian Ocean. However, the PCW run still outperforms the CTL and PC runs, showing a similar orbit to that in the MERRA reanalysis data.

From the analysis in this section, we can see that improvements in precipitation in the PCW run can be attributed to improvements in the covariation of moisture advection and dynamical convergence during the ISO, which, through the moisture–convection feedback mechanism (Jiang et al. 2004; Del Genio et al. 2012; Wang et al. 2015), is modulated by moistening associated with appropriate representation of convection (including convection intensity and shallow–deep convection transition) in the PCW run.

4. Conclusions

In this study, we modified the Plant–Craig stochastic deep-convection parameterization by linking the probability of occurrence of convective mass flux to large-scale vertical pressure velocity at 500 hPa each day. While it is based on radar observations of Gottwald et al. (2016), the rationale behind this modification is that large convective systems are more likely to occur under disturbed large-scale circulation conditions than under undisturbed circulation conditions. In comparison to the original PC scheme, the simulated climate mean states, including tropical precipitation, are comparable (Fig. 2) except for an enhancement of precipitation over the ISM region (Fig. 3). Since the ISM is degraded in the simulation using the PC scheme, this change is a desirable improvement. The simulation with the modified PC scheme (PCW) produces a more realistic annual cycle of rainfall over central India (Fig. 4a) and the ISM onset and withdrawal time (Fig. 5). This is probably because linking the probability of occurrence of convective cloud mass flux to in the stochastic convection scheme represents the systematic response of convection systems to the large-scale monsoon circulation better than the purely stochastic response in the original stochastic parameterization. It also helps further increase the moderate-to-intense precipitation over central India, making it closer to observations compared to the PC scheme (Fig. 4b). The ISM intraseasonal oscillations, including quasi-biweekly and 30–60-day modes, are investigated as well. Improvements using PCW are found in the simulation of northeasterward propagation of the 30–60-day mode, whereas the CTL and
PC runs show westward movement in contrast to the eastward propagation in the observations. PCW simulates the correct propagation direction east of 105°E and west of 75°E, although there is still a westward propagation between 75° and 105°E (Fig. 6). A possible explanation is offered following Wang et al. (2015), who examined the connections of cloud regimes to large-scale dynamical convergence in the ISO of the ISM. They found that over the Indian subcontinent stronger (weaker) low-level-scale dynamical convergence (or equivalently midtroposphere vertical velocity) often associated with more deep (shallow) convective clouds frequently occurs during the active (suppressed) phase of intraseasonal oscillation. Therefore, linking the probability of cloud mass flux to $a_{so}$ in the PC stochastic deep-convection parameterization appears to provide this convection–dynamics coupling in the GCM, leading to a better simulation of the ISO of the ISM. Through moistening associated with appropriate representation of convection in the PCW run and the interaction of convection and dynamics, it better represents the patterns and amplitudes of large-scale dynamical convergence and moisture advection during the ISO peaks and troughs (Figs. 10 and 11). Their gradual transitions between the ISM active and break phases are also realistically simulated, reproducing the preconditioning with positive moisture advection anomalies leading those of dynamical convergence by 4–6 days in the developing phase and negative moisture advection anomalies leading those of dynamical convergence by 6–8 days in the decaying phase (Fig. 12). These features make the PCW run successfully reproduce the clockwise trajectory in the moisture convergence–advection phase space of monsoon cycle over the Indian subcontinent signified by anomalies of dynamical convergence and moisture advection similar to that in the MERRA reanalysis data, while both CTL and PC show counterclockwise monsoon cycle (Fig. 13). Owing to the moisture–precipitation coupling, improvements in large-scale moisture during the ISO in the PCW run are also beneficial to improvements in precipitation (Figs. 3–7 and 9).

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