Impact of Stochastic Entrainment in the NCAR CAM Deep Convection Parameterization on the Simulation of South Asian Summer Monsoon

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Abstract

Model simulations are highly sensitive to the formulation of the atmospheric mixing process or entrainment in the deep convective parameterizations used in their atmospheric component. In this paper, we have implemented stochastic entrainment in the deep convection scheme of NCAR CAM5 and analyzed the improvements in model simulation, focusing on the South Asian Summer Monsoon (SASM), as compared to the deterministic entrainment formulation in the default version of the model. Simulations using stochastic entrainment (StochCAM5) outperformed default model simulations (DefCAM5), as inferred from multiple metrics associated with the SASM. StochCAM5 significantly alleviated some of the longstanding SASM biases seen in DefCAM5, such as precipitation pattern and magnitude over the Arabian Sea and western Equatorial Indian ocean, early monsoon withdrawal, and the overestimation (underestimation) in the frequency of light (large-to-extreme) precipitation. Related SASM dynamical and thermodynamical features, such as Somali Jet, low-level westerly winds, and meridional tropospheric temperature gradient (MTTG), are improved in StochCAM5. Further, the simulation of monsoon intra-seasonal oscillation (MISO), Madden Julian Oscillation (MJO), and equatorial Kelvin waves are improved in StochCAM5. Many essential climate variables, such as shortwave and longwave cloud forcing, cloud cover, relative and specific humidity, and precipitable water, show significant improvement in StochCAM5.
1. Introduction

The conventional global climate models (GCMs) have failed to adequately parameterize sub-grid scale cloud and convection processes that occur either in a small region or dissipate instantly (e.g., Jones and Randall 2011). Most current GCMs use a convection parameterization scheme that describes the ensemble mean effects of sub-grid scale convection and cloud processes at the resolved grid-scale while ignoring individual cloud variability (e.g., Palmer 2001; Lin and Neelin 2003; Langan et al. 2014). Previous research has shown that this missing variability is important for realistic simulation of tropical climate systems (e.g., Moncrieff et al. 2012; Waliser et al. 2012) and has used two distinct approaches to incorporate this heterogeneity in GCMs: super-parameterization and stochastic parameterization. For super-parameterization, a cloud-resolving model (CRM) that explicitly resolves sub-grid scale convective processes is used in each GCM grid (e.g., Grabowski and Smolarkiewicz 1999; Khairoutdinov and Randall 2001; Krishnamurthy et al. 2014). On the other hand, for stochastic parameterization, a stochastic term is used in a conventional parameterization scheme (e.g., Buizza et al. 1999; Bright and Mullen 2002; Lin and Neelin 2003; Shutts 2005; Khouider and Majda 2006; Plant and Craig 2008; Khouider et al. 2010; Dorrestijn et al. 2013; Deng et al. 2015). Jones et al. (2019a) developed a different variant of super-parameterization by incorporating multiple CRMs in each GCM grid and initializing each CRM with a unique set of random thermal perturbations (referred to as multiple-instance super-parameterization).

Compared to conventional convective parameterization, super-parameterization has made significant advances in weather and climate prediction, especially over the tropics. For example, super parameterization has significantly improved the simulations of Madden Julian Oscillation (MJO; Madden and Julian 1971), tropical precipitation, El-Niño southern oscillation, and tropical
cyclones (e.g., Khairoutdinov and Randall 2001; Benedict and Randall 2009, 2011; Stan et al. 2010; DeMott et al. 2011, 2013; Pritchard et al. 2011; Arnold et al. 2013; Krishnamurthy et al. 2014; Pritchard et al. 2014). Goswami et al. (2015) used super-parameterization in the CFSv2 model and reported an improved simulation of intra-seasonal oscillation (ISO) during the South Asian summer monsoon (SASM). However, super-parameterization simulations are computationally expensive, so their use is limited. On the other hand, stochastic parameterization simulations consume computational resources similar to conventional GCMs and outperform them. For example, Goswami et al. (2017a) used the stochastic multi-cloud model scheme (MCM; Khouider et al. 2010; Dorrestijn et al. 2013; Deng et al. 2015) in CFSv2 and reported an improved simulation of tropical synoptic and intra-seasonal variability. Several other researchers also incorporated a stochastic noise term into the grid-scale mean-field and noted an enhanced simulation of tropical diurnal variability and equatorial waves (e.g., Buizza et al. 1999; Bright and Mullen 2002; Lin and Neelin 2003; Shutts 2005; Berner et al. 2009). Wang et al. (2016a, b; 2017) used the stochastic approach of Plant and Craig 2008 in CAM5 to compute the properties of a plume of a given mass stochastically using the Poisson distribution, and they found an improved simulation of precipitation extremes and variability over the tropics.

While the above advances in climate modeling, precipitation biases over South Asia, equatorial Indian ocean (EIO), inter-tropical convergence zone (ITCZ), and South Pacific convergence zone (SPCZ) worsen (e.g., Wang et al. 2016a, 2017; Goswami et al. 2017a). Furthermore, simulations of precipitation extremes and inter-annual variability over the Indian subcontinent, quasi-biweekly oscillation (10-20 days), and MISO (30-60 days) need to be improved (e.g., Goswami et al. 2017a, b; Wang et al. 2018). Jones et al. (2019b) also found that
using the multiple-instance super-parameterization in GCMs did not improve the simulation of
MJO and equatorial waves.

Previous research has shown that an adequate representation of the interaction of sub-grid
scale cloud and convection processes with large-scale circulations can improve the ISO simulation
(e.g., Jiang et al. 2011; DeMott et al. 2011; Abhik et al. 2013). Wang et al. (2018) used the Plant
and Craig (2008) scheme in CAM5 to link the stochastic generation of convective clouds to large-
scale vertical velocity and reported an improvement in Indian summer monsoon (ISM) simulation
but a deterioration in precipitation simulation over the equatorial region. Siebesma et al. (2003)
shown that the variation in lateral entrainment rate (i.e., the interaction between the updrafts and
the environment) is critical for accounting variability between different updrafts and allowing
updrafts to terminate at different levels. It has been found to be sensitive to precipitation extremes,
cyclone intensity, climate variability, cloud feedbacks, and climate sensitivity (e.g., Held et al.
2007; Knight et al. 2007; Bechtold et al. 2008; Joshi et al. 2010; Yang et al. 2013; Sherwood et al.
2014; Qian et al. 2015; Kooperman et al. 2018). For example, Bush et al. (2014) shown that SASM
precipitation biases are highly sensitive to entrainment rate using the MetUM model. Oueslati and
Bellon (2013) shown that double ITCZ in the Pacific ocean is sensitive to the entrainment rate of
convective plumes in the CNRM-CM5 model and that increasing the entrainment rate resulted in
a significant reduction in double ITCZ and SPCZ related biases.

In general, several attempts have been made to improve entrainment formulations in GCMs
(e.g., Neggers et al. 2002; Siebesma et al. 2003; Rio et al. 2010), but most of them do not allow
for large variability of entrainment among different updrafts. For example, in Neggers et al. (2002),
the entrainment rate is assumed to be the inverse product of updraft vertical velocity and a constant
entrainment time-scale. This approach, however, is highly sensitive to the entrainment time-scale
specification, and all moist updrafts entrain the environmental air, resulting in a decrease in buoyancy and thereby restricting the updrafts from reaching to neutral buoyancy level (Romps and Kuang 2010). Raymond and Blyth (1986) proposed a different view of entrainment rate formulation that the variability in cloud updrafts can be represented by a stochastic entrainment rate, which has been investigated for shallow convective and non-precipitating convective boundary layer clouds using LES and single-column model (SCM) runs (e.g., Romps and Kuang 2010; Nie and Kuang 2012, Sušelj et al. 2013, 2014). Sušelj et al. (2013) used stochastic entrainment in an SCM above the condensation level (LCL) by assuming lateral entrainment as a discrete (rather than a continuous) process and a well-mixed environmental air in the dry updraft region (i.e., below LCL). As a result, the entrainment rate value in the dry updraft region is not sensitive to model results (could be seen in Sušelj et al. 2012) and is set to a constant value for simplicity. This implementation has improved the representation of convective boundary layer clouds in SCM through an improved simulation of turbulent fluxes. In addition to these stochastic entrainment-based LES and SCM runs, the implementation and evaluation of stochastic entrainment rate in a GCM must be thoroughly studied for realistic simulation of global and regional climate.

In this study, we implement a stochastic entrainment rate in CAM5’s deep convection scheme. In the deep convection scheme, the dilute convective available potential energy (CAPE) is calculated by assuming continuous atmospheric mixing at a constant entrainment rate (Neale et al. 2008). This dilute CAPE is further used in the closure assumption to estimate cloud-base updraft mass-flux and trigger mechanisms (Zhang and McFarlane 1995). As a consequence, implementing a stochastic entrainment rate in CAM5 would also result in stochasticity in closure and trigger mechanism. This study focuses on the impact of stochastic entrainment on SASM simulations as
part of an effort to improve SASM and India's climate simulations by the Department of Science
and Technology’s Centre of Excellence in Climate Modeling at the Indian Institute of Technology
Delhi (Dash et al. 2017). The manuscript is organized as follows: Section 1 presents an
introduction, Section 2 describes the model details, implementation approach, model simulations
and observational data, and Section 3 presents results and discussion. Particularly, in Section 3,
we discuss precipitation pattern in Section 3.1, moisture distribution in Section 3.2, cloud
properties in Section 3.3, low-level and upper-level wind distribution in Section 3.4, north-south
wavenumber frequency spectrum in Section 3.5, and east-west wavenumber frequency spectrum
in Section 3.6. Finally, Section 4 concludes the study.

2. Model Details, Implementation Approach, Simulations, and Observational Data

2.1 Model Details

For simulations, the NCAR Community Atmosphere Model version-5.3 (CAM5) is used
within the framework of Community Earth System Model version-1.2.2. In CAM5, the finite
volume dynamical core, moist turbulence scheme, and shallow convection scheme are used from
Lin (2004), Bretherton and Park (2009), and Park and Bretherton (2009, respectively. The revised
Zhang-McFarlane (1995) scheme by Neale et al. (2008) to account for the dilute CAPE
computation and by Richter and Rasch (2008) to account for the convective momentum transport
is used for the treatment of deep convection (hereafter, ZMNR). The stratiform microphysical
scheme from Morrison and Gettelman (2008), the ice crystal nucleation from Liu et al. (2007), and
the ice supersaturation from Gettelman et al. (2010) are used. The Rapid Radiative Transfer Model
(RRTM) is used to calculate the radiative fluxes (Iacono et al. 2008; Mlawer et al. 1997).
2.2 Implementation Approach

In CAM5, the ZMNR scheme is modified to account for the stochastic and discrete nature of the entrainment process, as compared to the prescribed constant entrainment rate across vertical levels. The stochastic entrainment approach used in this paper closely follows the approach used by Sušelj et al. (2013) for convective boundary layer clouds in SCM. We also use Romps and Kuang’s (2010) findings that the model results are unaffected by changes in entrainment values below LCL (i.e., in dry updrafts that have a well-mixed environmental air). As a result, the entrainment rate ($\varepsilon$) below LCL is set to a constant value of $0.1 \times 10^{-3} \text{ m}^{-1}$, which is the entrainment rate used in CAM5 (Neale et al. 2008), and the stochastic entrainment rate above the LCL is implemented in the manner described by Sušelj et al. (2013).

For a small distance $dz$ ascends of updrafts above LCL, the probability of an entrainment event is determined by a random number ($\beta$) drawn from the Bernoulli distribution with a value of zero (representing no entrainment event) or one (representing an entrainment event) with a probability equal to $dz/L_0$, where $L_0$ represents the average distance that the updrafts must traverse to entrain once (or the average distance between two entrainment events). Sušelj et al. (2013) assumed that the fractional entrained mass flux at each entrainment event is proportional to the vertical mass flux of updrafts and equal to $\varepsilon_u M_u$. These assumptions are used to parameterize entrainment rate, as shown in Eq. 1.

$$\varepsilon = s \varepsilon_u B \left( \frac{dz}{L_0} \right).$$  

Further, for a finite distance $\Delta z$ ascends of updrafts, the number of entrainment events is determined by a random number ($\varphi$) drawn from the Poisson distribution with a probability equal to $\Delta z/L_0$, and the profile of entrainment rate is parameterized as shown in Eq. 2.

$$\varepsilon(\Delta z) = \frac{1}{\Delta z} \varepsilon_u \varphi \left( \frac{\Delta z}{L_0} \right).$$
where, $\frac{1}{\Delta z}$ is the shape parameter since the entrainment profile varies more steeply with height.

Based on sensitivity studies for $\varepsilon_d$ and $L_0$ conducted over the SASM and global region, as well as previous studies (Sušelj et al. 2013; Romps and Kuang 2010), the value of $L_0$ and $\varepsilon_d$ are prescribed to $\varepsilon_d = 0.2$ and $L_0 = 100$ m (i.e., each event leads to entrainment of ~20% of the vertical mass flux over an average distance of $L_0 = 100$ m). For simplicity, the distance $\Delta z$ is considered here as the difference between two vertical model levels. The complete structure of the stochastic entrainment is shown in Figure 1. From the sensitivity studies (see Supp. Figure S1), changing $\varepsilon_d$ and $L_0$ from their original value at the same time has no significant effect on the model results. For example, changing $\varepsilon_d$ and $L_0$ values together from (i) $\varepsilon_d = 0.1$ and $L_0 = 300$ to $\varepsilon_d = 0.2$ and $L_0 = 600$, and (ii) $\varepsilon_d = 0.1$ and $L_0 = 500$ to $\varepsilon_d = 0.2$ and $L_0 = 1000$ results in no significant change in the vertical velocity and humidity over the tropical region. On the other hand, the simulation performed by fixing any one of these parameters ($\varepsilon_d$ or $L_0$) at a time and varying the other parameter shows changes in vertical velocity and humidity distribution. As a result, we anticipate that the model results would be generally sensitive to a single parameter (i.e., either $\varepsilon_d$ or $L_0$) affecting the entrainment rate.

### 2.3 Simulations and Observational Data

We performed two CAM5 simulations, one with the default ZMNR (DefCAM5) and the other with the stochastic ZMNR (StochCAM5). Each simulation is run for 13-years at a horizontal resolution of 0.9° latitude and 1.25° longitude, and 30 vertical levels, with the prescribed climatological monthly sea surface temperature. The first year of simulation is used as a spin-up period, and the remaining 12-years data are used for analysis.
The following observations and reanalysis data are used in this study for model evaluation:

- the Global Precipitation Climatology Project (GPCP; Adler et al. 2003) for monthly total precipitation, the Tropical Rainfall Measuring Mission (TRMM) 3A12 for monthly convective and large-scale precipitation (Kummerow et al. 1998) and 3B42 for daily total precipitation (Huffman et al. 2007). The monthly convective precipitation for GPCP is computed using the total to convective precipitation ratio from TRMM 3A12 (see Pathak et al. 2019 for the methodology used for calculation), and the corresponding large-scale precipitation is obtained by taking out the convective component from total precipitation. In addition, we also use the Clouds and Earth's Radiant Energy System-Energy Balanced and Filled (CERES-EBAF; Loeb et al. 2009) project for shortwave cloud forcing (SWCF) and longwave cloud forcing (LWCF), the National Aeronautics and Space Administration (NASA) Water Vapor Project (NVAP; Randel et al. 1996) for precipitable water and liquid water path, and the high-resolution data series of International Satellite Cloud Climatology Project (ISCCP; Young et al. 2018) for low, middle, high, and total cloud fraction. The horizontal and vertical wind, air temperature, relative humidity, and specific humidity are obtained from the ECMWF reanalysis (ERA-I; Dee et al. 2011). These observed or reanalysis datasets are first linearly interpolated to model resolution, and the climatological mean of these datasets is used for this study.

3. Results and Discussion

The DefCAM5 and StochCAM5 simulations are evaluated using the Taylor diagram over the tropics (Figure 2) and Table 1 over the SASM region. Overall, StochCAM5 outperforms DefCAM5 in simulating the oceanic rainfall, shortwave cloud forcing (SWCF), longwave cloud forcing (LWCF), zonal wind at 850 hPa, and vertical wind at 500 hPa over the tropical and SASM
region. The frequency distribution of percentage bias for annual mean precipitation (Figure 3) shows that the frequency of large percentage bias (greater than 60%) does not differ much between StochCAM5 and DefCAM5, except for a decrease (increase) in the frequency of moderate percentage bias (30-60%) over tropical land (ocean) in StochCAM5. For the seasonal mean (June-August) precipitation, the frequency of moderate percentage bias (30-60%) and small percentage bias (less than 30%) is greatly reduced over the tropical land but greatly increased the frequency of small percentage bias over the tropical ocean. In general, the large increase in the frequency of small percentage bias over the tropical ocean leads to a significant improvement in precipitation during the SASM period.

3.1 Precipitation Pattern

Figure 4 shows the spatial distribution of JJAS mean total, convective, and large-scale precipitation from observations and simulations, as well as their differences. The simulated total precipitation pattern from DefCAM5 and StochCAM5 is found to be comparable to observations, with average values of 4.06, 4.96, and 5.01 mm/day over the tropical region for observations, DefCAM5, and StochCAM5, respectively. The large overestimation over the Arabian Sea (AS), western Indian ocean, and underestimation over the north-east Bay of Bengal (BoB), northeast India, and Indo-Burmese mountains in DefCAM5 are significantly alleviated in StochCAM5, but the overestimation over the leeward side of the Western Ghats (WG) is significantly deteriorated. StochCAM5 also shows a decrease in total precipitation overestimation over SPCZ and ITCZ in the Pacific ocean. These improvements in total precipitation simulation from StochCAM5 are found due to an improved partitioning between convective and large-scale precipitation. For example, StochCAM5 reduces the convective precipitation overestimation and large-scale
precipitation underestimation over the majority of South Asia. With StochCAM5, an increase in
pattern correlation (PCC) and a decrease in root mean square error (RMSE) are also found for total
precipitation (PCC: 0.68; RMSE: 2.96 mm/day), convective precipitation (PCC: 0.74; RMSE: 2.48
mm/day) and large-scale precipitation (PCC: 0.42; RMSE: 2.04 mm/day) as compared to
DefCAM5 for total precipitation (PCC: 0.63; RMSD: 3.03 mm/day), convective precipitation
(PCC: 0.67; RMSE: 2.81 mm/day) and large-scale precipitation (PCC: 0.34; RMSE: 2.16 mm/day)
(Figure 4). This is advantageous to the model because the total precipitation biases over South
Asia have been a longstanding problem in CAM5 and its predecessors (e.g., Wang et al. 2016a;
Anand et al. 2018; Mishra et al. 2018), as well as in CMIP5 (e.g., Sperber et al. 2013). It was not
greatly alleviated, even after including stochasticity in the generation of convective clouds (Wang
et al. 2016a) and linking it to large-scale vertical velocity (Wang et al. 2018). Further breaking
convective precipitation into contributions from the deep and shallow convections (Supp. Figure
S2), we find a significant decrease (increase) in deep (shallow) convection over South Asia, except
the WG, northeast India, and Indo-Burmese mountains, which show an increase in deep convection
in StochCAM5 as compared to DefCAM5. As a result, the improvement in total precipitation
simulation over the AS and western Indian ocean from StochCAM5 is due to a decrease in
convective precipitation from deep convection, while the worsening over the leeward side of WG
is due to an increase in convective precipitation from both deep and shallow convections.

In regard to the annual cycle of total precipitation over the Indian land, both DefCAM5
and StochCAM5 simulate an earlier monsoon onset (in May), earlier peak precipitation (in mid-
June to early-July), and a larger peak precipitation magnitude with respect to observations (Figure
5a). However, as compared to DefCAM5, the monsoon withdrawal date (~10 days earlier in
DefCAM5) is improved in StochCAM5, but the monsoon onset date (~10 days earlier in
DefCAM5) is simulated similar to DefCAM5 with no discernible change (see section 3.4 and Figure 13 for more details), and the peak precipitation magnitude is worsened (approximately 25% greater) in StochCAM5 than DefCAM5 (Figure 5a). The overall deterioration of the annual cycle of total precipitation is largely coming from the Western Ghats due to a large increase in both deep convective precipitation and large-scale precipitation. We speculate that this increase is associated with the corresponding increase in moisture flux convergence (Supp. Figure S3), which is followed by higher deep convection and latent heat release and a positive feedback cycle leading to further convergence and a further increase in total precipitation.

Further, the frequency distribution of precipitation rate (Figure 5b) shows that the frequency of light precipitation rate (1-10 mm/day) and moderate precipitation rate (10-20 mm/day) in DefCAM5 is overestimated, while the frequency of very heavy (extreme) precipitation rate (greater than 40 mm/day) is underestimated (also seen in CMIP5 models by Jain et al. 2019 and Salunke et al. 2019). StochCAM5 improves the frequency distribution of precipitation rate, as well as the contributions of light to extreme precipitation rates to total precipitation (Figure 5c). The improved frequency distribution in StochCAM5 could be to the improved sub-grid scale process representation by launching convective clouds with stochastically varying entrainment rates. The improvement in the frequency distribution of precipitation has also been noted by linking the stochastic Plant and Craig (2008) scheme to large-scale vertical velocity (Wang et al. 2018).

3.2 Moisture Distribution

Figure 6 shows the JJAS mean vertical cross-section of specific humidity and relative humidity from ERA-I and model simulations, as well as their differences, over 0°-30°N.
DefCAM5 shows a positive bias over 40°-70°E and a negative bias over 70°-140°E in the entire troposphere for specific humidity. StochCAM5 alleviates the positive and negative biases seen in DefCAM5 for specific humidity, resulting in a better simulation of specific humidity over the above regions (Figure 6a-c). For relative humidity, StochCAM5 shows a decrease in positive bias over 40°-65°E and a negative bias over 90°-120°E seen in DefCAM5. However, StochCAM5 also shows a deterioration in positive bias over 120°-140°E below 800 hPa for relative humidity (Figure 6d-f).

Figure 7 shows the JJAS mean total column water vapor (CWV) from NVAP observations and simulations, as well as their differences. DefCAM5 and StochCAM5 both underestimate the CWV over the Indian land, BoB, central and eastern parts of the EIO, and western Pacific ocean, while overestimating the CWV over the Arabian Peninsula, Tibetan region, western AS, and southern Indian ocean. When compared to DefCAM5, StochCAM5 decreases CWV biases over the western AS, southern Indian ocean, and western Pacific ocean while slightly increasing the CWV biases over the Indian land. Overall, the average CWV value over South Asia has been reduced from 42.03 mm in DefCAM5 to 41.99 mm in StochCAM5, resulting in better agreement with 41.84 mm in NVAP observation. In addition, the RMSE of CWV over South Asia has been decreased from 4.9 mm in DefCAM5 to 4.74 mm in StochCAM5. These CWV improvements are caused by a better distribution of specific humidity from 800 to 200 over western AS and the southern Indian ocean and surface to 600 hPa over BoB and the western Pacific ocean (Figure not shown).
3.3 Cloud Properties

To understand the factors that influence precipitation and water vapor, we analyze the changes in cloud properties induced by stochastic entrainment. Since the cloud microphysical processes associated with cloud liquid water and ice are used in CAM5 to calculate large-scale precipitation from stratiform clouds (Morrison and Gettelman 2008), in Figure 8, we show the JJAS mean cloud liquid water path (LWP) over South Asia from NVAP observations and simulations, as well as their differences, and in Figure 9, we show the ice water path (IWP) difference between StochCAM5 and DefCAM5. Figure 8 shows that DefCAM5 highly underestimates LWP over northern BoB, eastern EIO, and western Pacific ocean. StochCAM5, on the other hand, alleviates DefCAM5’s LWP underestimation over northern BoB, AS, and western Pacific ocean, making it closer to NVAP observations. In addition to the above improvements in LWP, StochCAM5 also shows a deterioration in LWP over the western Indian ocean. Figure 10 shows that in StochCAM5, there is a decrease in IWP over the majority of South Asia, with a significant decrease over the western Indian ocean and an increase over WG and northeast India. Overall, the regions of increased LWP and IWP correspond well to regions of increased large-scale precipitation (Figure 4l).

Further, we show the difference in detrained liquid water (DLW) and detrained ice water (DICE) over South Asia in Figure 10a, since the DLW and DICE from deep and shallow convection relate to LWP and IWP in large-scale stratiform clouds and convective clouds (e.g., Morrison and Gettelman 2008; Wang et al. 2016a). We find that StochCAM5 has increased DLW from shallow convection. As this increased DLW is fed into the cloud microphysical parameterization as a source for large-scale cloud ice and water, it increases LWP and IWP (Morrison and Gettelman 2008), and thus the large-scale precipitation. Besides that, StochCAM5
has increased the convective mass flux for shallow convection (and thus the increased DLW) and
decreased it for deep convection (Figure 10b), resulting in increased shallow convective clouds
and decreased deep convective clouds (Figure 10c). These changes in clouds are also reflected in
the increased precipitation from shallow convection and the decreased precipitation from deep
convection in StochCAM5 (Supp. Figure S2). From Supp. Figure S4, we find that StochCAM5
decreases the frequency of occurrence of deep convection while increasing the frequency of
occurrence of shallow convection over the tropical and southern subtropical regions. We speculate
this could be due to the increased entrainment rate, which results in low buoyancy (as seen from
CAPE; Supp. Figure S4) and thus decreased deep convection and moisture in the middle to high
levels. Zhang and Mu (2005) also showed that the reduced deep convection favors the build-up of
CAPE, which could lead to an increase in the frequency of occurrence of shallow convection.
Furthermore, the large decrease in ice clouds in the upper troposphere in StochCAM5 is found to
decrease the total cloud ice amount, and possibly it could be one of the reasons for a large decrease
in IWP over the majority of South Asia (Figure 10c,d).

Figure 11 shows the JJAS mean low, middle, high, and total cloud cover from ISSCP
observations and simulations, as well as their differences. In DefCAM5, the low, middle, and high
clouds are all overestimated over the Indian land, western and equatorial Indian ocean (Figure 11e-
g). However, in StochCAM5 (Figure 11i-k), these overestimations are reduced, particularly in the
middle clouds, which are reduced by more than 10% over the western and equatorial Indian ocean,
and the high clouds, which are reduced by more than 5% over the Indian land (Figure 11m-o).
Thus, the pattern of changes in total clouds is dominated by the changes in middle clouds over the
western and equatorial Indian ocean and high clouds over the Indian land (Figure 11p). These
changes in the cloud cover in StochCAM5 can also be seen from a relative decrease in relative
humidity in middle and high levels (Figure 6f) and the reduced rate of heating and drying the troposphere over 40°-70°E from the moist processes (Supp. Figure S5). This reduced rate of heating and drying the troposphere is arising from the decreased convective updraft mass flux (Figure not shown). Since changes in LWP, IWP, and cloud fraction influences the cloud radiative effects, we find in Supp. Figure S6 that the large negative (positive) bias seen in DefCAM5 over the western Indian ocean and AS in SWCF (LWCF) is significantly alleviated in StochCAM5, with one possible reason being the reduced rate of heating and drying the troposphere (Jones et al. 2019b).

### 3.4 Low-level and Upper-level Wind

Since the changes in low-level and upper-level wind circulations during JJAS influence the moisture transport and precipitation over the ISM region, and hence, we analyze the low-level (850 hPa) and upper-level (200 hPa) wind circulations from ERA-I and simulations. Both model simulations capture the prime features of low-level wind circulation seen in observation, although with few biases in amplitude and spatial extent (Figure 12a-c). For example, the Somali jet (SJ) and low-level westerly wind over peninsular India and BoB are weaker in DefCAM5, but they are better simulated in StochCAM5 and comparable to ERA-I. In the upper-level wind circulation, DefCAM5 shows a large underestimation in the tropical easterly jet (TEJ) and overestimation in the subtropical westerly jet (STJ). In comparison to DefCAM5, the simulation of STJ is slightly improved, and the simulation of TEJ is deteriorated in StochCAM5 (Figure 12d-f).

To better understand the physical cause of these changes in wind circulation, we show the annual cycle of 600-200 hPa averaged meridional tropospheric temperature gradient (MTTG) between the two boxes, one over 5°N-35°N and 40°E-100°E and other over 5°N-15°S and 40°E-
100°E (Figure 13). These two boxes represent the large-scale temperature gradient zones that are responsible for the wind reversal from north-easterly to south-westerly and maintaining the south-westerly wind flow during JJAS (e.g., Webster et al. 1998; Goswami and Xavier 2005; Goswami and Chakravorty 2017). Overall, both model simulates MTTG comparable to ERA-I, but the MTTG reversal from negative to positive and (positive to negative) is ~10 days earlier in DefCAM5 as compared to the observed negative to positive (positive to negative) reversal in ~1st June (~1st October), making the monsoon circulation weaker followed by an early onset and withdrawal of monsoon by ~10 days. The monsoon onset and withdrawal date are defined when MTTG annual cycle changes from negative to positive and positive to negative value, respectively (Goswami and Chakravorty 2017). On the other hand, StochCAM5 simulates the annual cycle of MTTG very similar to ERA-I, except the reversal of negative to positive that is still earlier ~8 days (Figure 13). In StochCAM5, the reversal of MTTG from positive to negative is simulated similarly to ERA-I, resulting in a monsoon withdrawal close to the observed date (~1st October) (e.g., Xavier et al. 2007; Ashfaq et al. 2009). This improvement in MTTG annual cycle in StochCAM5 is thought to be a possible reason for an improvement in SJ and low-level westerly wind. These MTTG changes may be attributed to enhanced regional Hadley circulation (Figure not shown) that improves the meridional and vertical energy transport (Gadgil 2018). Supp. Figure S7 shows the spatial pattern of JJAS mean tropospheric temperature averaged over 700-300 hPa for ERA-I and model simulations. As compared to DefCAM5, StochCAM5 shows a 0.5 K increase in warm bias over the Tibetan region and a 0.25 K increase in cold bias over the southern Indian ocean, indicating an increased north-south temperature gradient and thus a small increase in MTTG peak during JJAS (Figure 13).
3.5 North-South Wavenumber-Frequency Spectrum

The pronounced 30-60 day oscillations of northward propagating convection anomalies from EIO to ISM region during JJAS is recognized as a unique feature of monsoon intra-seasonal oscillation (MISO; Joseph et al. 2009; Joseph et al. 2012; Suhas et al. 2012; Abhik et al. 2013; Sharmila et al. 2013; Abhilash et al. 2014). It accounts for ~ 20% of total rainfall variance over the Indo-Pacific region and linked to active and break spells of ISM (e.g., Goswami et al. 2011; Suhas et al. 2013). Hence, the north-south wavenumber frequency spectrum is analyzed during JJAS over the ISM region (65°E-90°E; 15°S-30°N) to investigate how well the DefCAM5 and StochCAM5 simulate MISO in comparison to observations. Figure 14a-c shows JJAS north-south space-time spectra of daily precipitation from TRMM and simulations. TRMM shows a dominant northward propagating mode of 30-60 day period at wavenumber 1 with maximum power at 45 days (Figure 14a). Compared to TRMM, DefCAM5 failed to capture the MISO signal at wavenumber 1 (Figure 14b), while StochCAM5 captures it at wavenumber 1 with maximum power at ~50 days (Figure 14c). Further, we compute the ratio of northward and southward power of the precipitation spectrum averaged over 30-90 day period to verify the fraction of meridionally propagating MISO (Figure 14d-f). TRMM shows that the northward power is greater than the southward power at wavenumber 1, while the northward and southward power are nearly equal at all other wavenumbers. DefCAM5 failed to simulate the correct ratio as noticed before, exhibiting higher power for southward not only at wavenumber 1 but also at wavenumber 2. On the other hand, StochCAM5 simulates greater power in northward than southward at wavenumber 1 and 2, but the simulated power is lesser than TRMM.

Furthermore, from the analysis of underlying mechanisms for MISO, we find that the MISO improvement in StochCAM5 is likely due to the improvement in the simulation of
atmospheric internal dynamics associated with vertical easterly wind shear over the Indian latitudes (Supp. Figure S8; e.g., Jiang et al. 2004; Drbohlav and Wang 2005; Sharmila et al. 2013), and this improvement in MISO could be another reason for the improvements in seasonal mean rainfall (e.g., Abhik et al. 2013; Abhilash et al. 2014).

3.6 East-West Wavenumber-Frequency Spectrum

Figure 15 shows the symmetric component of the normalized power spectrum of daily total precipitation averaged over 15°S-15°N during JJAS from TRMM and simulations, using the methodology of Wheeler and Kiladis (1999). This figure shows the eastward and westward propagation of convective anomalies associated with MJO and equatorial waves (e.g., Kelvin and Rossby waves). Previous studies have shown that the zonally (east-west) propagating disturbances travel along the equator and significantly affect the synoptic variability in the tropics. Thus, from figure 15, for MJO, the observed eastward propagating mode with 30-70 days period and wave number 1-5 is found to be weaker simulated (shorter in periodicity and lesser in power, with maximum power only in the zonal wavenumber range of 1-1.5) in DefCAM5, while, it is found to be better simulated with enhancement in power in the zonal wavenumber range of 1-4 in StochCAM5 with an average periodicity of ~30-70 days. This improvement is expected to be arising from increased shallow convection (Zhang and Mu 2005), which helps to precondition the lower troposphere for MJO (e.g., Zhang and Song 2009; Wang et al. 2016b). The power of eastward propagating Kelvin wave is found to be better simulated for lower frequencies (5-25 days) at shorter zonal wave-numbers, but the power at higher frequencies for higher zonal wave-numbers is even more underestimated in StochCAM5. Furthermore, for the Rossby wave, a westward propagating wave with periodicity 10-45 days and zonal wavenumber (-1 to -10) is
simulated comparable to TRMM, however, the spectral power at smaller zonal wavenumber (-1 to -6) is slightly underestimated in both model simulations.

4. Conclusions

In this study, we modified the deterministic ZMNR deep convection parameterization scheme by stochastically formulating the entrainment rate. Two simulations, one with default scheme (DefCAM5) and other with modified scheme (StochCAM5), were performed using NCAR-CAM5. Statistical evaluation metrics computed for these simulations showed that StochCAM5 outperforms DefCAM5 in simulating mean annual and seasonal climate states on both global and regional scales (South Asia). Specifically, StochCAM5 significantly alleviates the South Asian summer monsoon related biases, such as:

- The total precipitation overestimation over AS, northeast India, EIO, MC, and the underestimation over central India, BoB, Burmese mountains, Myanmar, and WPO
- The early retreat of monsoon from Indian land
- The overestimation in the frequency of light to moderate precipitation and underestimation in the frequency of extreme precipitation.

These biases have been longstanding concerns in climate modeling, and their improvement will play a crucial role in the simulation of the current climate, process studies, and future climate change projections (e.g., Sperber et al. 2013; Sabeerali et al. 2014; Wang et al. 2018). These improvements in StochCAM5 are due to improved representation of convective clouds by launching clouds with stochastic entrainment rates. In addition to total precipitation, StochCAM5 also improves its partitioning between convective and large-scale precipitation components. Improvement in convective precipitation is through the large change in deep- and moderate change
in shallow-convective precipitation, while improvement in large-scale precipitation is through improved cloud microphysical properties via LWP (Morrison and Gettelman 2008). Cloud forcing, cloud cover fractions, relative humidity, specific humidity, and precipitable water from StochCAM5 are also considerably improved over South Asia for JJAS.

As for the above improvements, StochCAM5 also enhances the large-scale dynamics associated with it. Improved SJ and low-level westerly wind boost the moisture transport from the ocean to the Indian sub-continent (e.g., Findlater 1969), resulting in reduced precipitation biases. The worsening of overestimated precipitation over peninsular India in StochCAM5 as compared to DefCAM5 is due to the strengthening of TEJ and its influence on the low-level westerly jet, thus causing more precipitation over peninsular India and less moisture transport over the core monsoon region (Koteswaram 1958; Sathiyamoorthy 2005; Sreekala et al. 2013). Improvement in large-scale MTTG through the enhancement of meridional and vertical energy transport (Gadgil 2018) could be the major reasons for the improvement in low-level wind circulation (e.g., Goswami and Xavier 2005). This improvement in MTTG enhances the atmospheric instability and convection over the core monsoon region (Zhou and Murtugudde 2014), and hence the improvement in ITCZ (e.g., Gadgil 2018) and monsoon withdrawal (e.g., Xavier et al. 2007; Ashfaq et al. 2009).

StochCAM5 has also substantially improved the simulation of MISO, MJO, and planetary-scale equatorial Kelvin waves for higher periodicity days. Thus, we find that although the implementation of stochasticity in cloud entrainment in the deep convection parameterization led to the improvement in multiple climate phenomena, both globally and over South Asia, there still remain biases, suggesting the need for further model development.
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Data Availability

The observed data used in this study is publicly available and the model simulated data can be obtained from the corresponding author.

Code Availability

The climate model used for simulations are freely available at https://www.cesm.ucar.edu/ and the code used for figure generation is available with corresponding author and can be obtained on request.

Conflict of interest

The authors declare no competing interests.
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|                           | Obs/ERA-I Mean | DefCAM5 Mean (StochCAM5) | Pearson Pattern Correlation | Normalized Standard Deviation | Percentage Bias | RMSE     |
|---------------------------|----------------|--------------------------|-----------------------------|-------------------------------|-----------------|----------|
| Land Rainfall             | 3.91           | 4.62 (5.02)              | 0.68 (0.70)                 | 1.16 (1.33)                   | 17.95 (29.29)   | 3.37 (3.73) |
| Ocean Rainfall            | 4.13           | 5.15 (5.00)              | 0.58 (0.70)                 | 0.83 (0.82)                   | 24.79 (21.58)   | 2.83 (2.43) |
| SWCF                      | -50.35         | -62.91 (-59.98)          | 0.81 (0.83)                 | 1.09 (1.08)                   | 24.96 (19.13)   | 22.67 (20.26)|
| LWCF                      | 35.59          | 35.19 (32.61)            | 0.82 (0.86)                 | 0.89 (0.82)                   | -1.11 (-8.35)   | 12.14 (11.03)|
| Land 2-m Temperature      | 24.02          | 24.74 (24.80)            | 0.94 (0.94)                 | 1.04 (1.07)                   | 2.97 (3.25)     | 2.73 (2.77) |
| T (1000-100 hPa)          | 26.56          | 24.65 (24.69)            | 0.46 (0.47)                 | 1.35 (1.38)                   | -7.21 (-7.05)   | 5.18 (5.21)  |
| Relative Humidity (1000-100 hPa) | 71.78 | 72.09 (71.92) | 0.91 (0.91) | 0.99 (1.00) | 0.45 (0.20) | 7.46 (7.39) |
| Zonal Wind at U850        | 4.36           | 0.23 (.05)               | 0.95 (0.96)                 | 1.08 (1.12)                   | -105.36 (98.83) | 4.88 (4.65) |
| Vertical Wind at 500 hPa  | -0.027         | -0.017 (-0.02)           | 0.36 (0.40)                 | 0.70 (0.73)                   | -35.65 (-37.49) | 0.05 (0.05)  |
Figure 1: Structure of the stochastic entrainment rate implemented in the ZMNR deep convection scheme. Entrainment rate ($\varepsilon$) from the parcel launch level to lifting condensation level (LCL) is kept the same as default value $\varepsilon(\Delta z) = 0.1 \times 10^{-3} \text{ m}^{-1}$. Entrainment above LCL is stochastically computed until the level of neutral buoyancy (LNB). The levels used here are the default model levels and the distance $\Delta z$ is the difference between the two model levels.
Figure 2: Taylor diagram with metrics for DefCAM5 and StochCAM5 over the tropics (30°S-30°N). The specific humidity (point 6) and temperature (point 7) are the mass-weighted vertical average from 1000-100 hPa. The four metrics used here are the Pearson correlation coefficient (represented by the cosine of the angle from the horizontal axis), the centered root mean square error (represented by the distance from the point on the horizontal axis defined as the reference point or REF), the normalized standard deviation (represented by the radial distance from the origin), and the percentage error (represented by the size of markers).
Figure 3: The frequency distribution of percentage bias for annual and seasonal (JJA and DJF) mean precipitation over the tropical land and ocean (30°S-30°N) from DefCAM5 and StochCAM5, as well as their differences. The 5% bin interval is used in computing the frequency of percentage bias.
Figure 4: Spatial variation of JJAS mean precipitation. a-c shows the JJAS mean (a) total precipitation, (b) convective precipitation and c) large-scale precipitation from GPCP observations over the tropics. d-f and g-i shows the difference in total, convective, and large-scale precipitation for DefCAM5 and StochCAM5 with respect to observations, respectively over the tropics. j-l shows the difference in total, convective, and large-scale precipitation for StochCAM5 with respect to DefCAM5 over South Asia (the zoomed region in black rectangle). The average value (Ave.), correlation (Corr.), and the root mean square difference (RMSD) for precipitation over South Asia are also shown at the bottom of a-i. Hatching (stippling) shows the differences which are improved (deteriorated) at 95% confidence level (two-tailed student t-test) in StochCAM5 with respect to DefCAM5.
Figure 5: (a) annual total precipitation cycle, (b) frequency distribution of daily precipitation rate over the Indian land during JJAS, and c) amount of precipitation falling in each bin of precipitation rate over the Indian land during JJAS.
Figure 6: The JJAS meridional mean cross sections of (a-c) specific humidity and (d-f) relative humidity in belt of Indian latitudes (0°-30°N) for (a, d) ERA-I, (b, e) DefCAM5 -ERA-I, and (c, f) StochCAM5 –DefCAM5. Hatching (stippling) shows the differences which are improved (deteriorated) at 95% confidence level in StochCAM5 with respect to DefCAM5. Q – specific humidity; RH – relative humidity.
Figure 7: JJAS mean total column water vapor over South Asia for (a) NVAP, (b) DefCAM5, and (c) StochCAM5 as well as their differences for (d) DefCAM5 – NVAP, (e) StochCAM5 – NVAP, and (f) StochCAM5 - DefCAM5. Hatching (stippling) shows the differences which are improved (deteriorated) at 95% confidence level in StochCAM5 with respect to DefCAM5. NVAP - National Aeronautics and Space Administration (NASA) Water Vapor Project.

Figure 8: JJAS mean total liquid water path (LWP) over South Asia for (a) NVAP, (b) DefCAM5, and (c) StochCAM5 as well as their differences for (d) DefCAM5 – NVAP, (e) StochCAM5 – NVAP, and (f) StochCAM5 - DefCAM5. Hatching (stippling) shows the differences which are improved (deteriorated) at 95% confidence level in StochCAM5 with respect to DefCAM5.
Figure 9: JJAS mean difference of ice water path (IWP) over South Asia between StochCAM5 and DefCAM5. The stippled regions show the differences which are significant at 95% confidence level.
Figure 10: JJAS mean difference of (a) detrained liquid water (DLW) and detrained ice (DICE) from deep and shallow convection, (b) updraft mass flux (UMF), downdraft mass flux (DMF), convective mass flux (CMF) for shallow and deep convection, (c) cloud cover distribution of ice, deep, shallow, and total cloud, and (d) cloud liquid and cloud ice amount over South Asia.

Figure 11: JJAS mean low, middle, high, and total cloud cover distribution over South Asia for (a-d) ISCCP, (e-h) DefCAM5, and (i-l) StochCAM5, as well as the difference for (m-p) StochCAM5 - DefCAM5. Hatching (stippling) shows the differences which are improved (deteriorated) at 95% confidence level in StochCAM5 with respect to DefCAM5. ISCCP - International Satellite Cloud Climatology Project.
Figure 12: JJAS mean (a-c) low-level wind at 850 hPa and (d-f) upper-level wind at 200 hPa for (a, d) ERA-I, (b, e) DefCAM5, and (c, f) StochCAM5.

Figure 13: The annual cycle of meridional tropospheric temperature gradient (MTTG) for ERA-I (red), DefCAM5 (green), and StochCAM5 (blue). MTTG is estimated by taking the difference of vertically averaged (600-200 hPa) temperature between the two boxes – one over 5°-35°N and 40°-100°E and other over 5°N-15°S and 40-100°E. MTTG also defines the monsoon onset date.
when this changes the sign from negative to positive on the annual cycle and the vice-versa for the monsoon withdrawal.

Figure 14: The north-south wavenumber-frequency spectra of precipitation during JJAS for (a) TRMM, (b) DefCAM5, and (c) StochCAM5 over the domain of 15°S-30°N and 60°-95°E. The power of precipitation spectrum separated as the northward and southward component, which is calculated from the north-south wavenumber-frequency spectra of precipitation averaged over 30-90 days period for (d) TRMM, (e) DefCAM5, and (f) StochCAM5.
Figure 15: The symmetric component of Wheeler-Kiladis space-time power spectrum for (a) TRMM, (b) DefCAM5, and (c) StochCAM5. It is computed from the daily time-series of total precipitation in the global belt of equatorial region (15°N-15°S) during JJAS.