

<sup>1</sup> **Improving Synoptic and Intra-Seasonal Variability in**  
<sup>2</sup> **CFSv2 via Stochastic Representation of Organized**  
<sup>3</sup> **Convection**

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4 To better represent organized convection in the Climate Forecast System  
5 version-2 (CFSv2), a stochastic multi-cloud model (SMCM) parameteriza-  
6 tion is adopted and a 15 year climate run is made. The last 10 years of sim-  
7 ulations are analyzed here. While retaining an equally good mean state (if  
8 not better) as the parent model, the CFS-SMCM simulation shows signif-  
9 icant improvement in the synoptic and intra-seasonal variability. The CFS-  
10 SMCM provides a better account of convectively coupled equatorial waves  
11 and the Madden-Julian oscillation (MJO). The CFS-SMCM exhibits improve-  
12 ments in northward and eastward propagation of intra-seasonal oscillation  
13 of convection including the MJO propagation beyond the maritime conti-

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14 nent barrier, which is the Achilles Heal for coarse resolution GCMs. The dis-  
15 tribution of precipitation events is better simulated in CFSsmcm and spreads  
16 naturally towards high precipitation events. Deterministic GCMs tend to sim-  
17 ulate a narrow distribution with too much drizzling precipitation and too  
18 little high precipitation events.

## 1. Introduction

19 Tropical convection is comprised of clouds of different scales and is a manifestation of  
20 their interaction across scales [Moncrieff *et al.*, 2012]. Efforts to adequately represent these  
21 convective systems in a global climate model (GCM) has led the scientific community to  
22 think beyond conventional convective parameterization schemes (CCPS). Superparama-  
23 terized GCMs (SP-GCM) [Grabowski, 2001; Khairoutdinov and Randall, 2001] and global  
24 cloud resolving models (GCRM) [Satoh *et al.*, 2005] (also see Randall [2013] for a review)  
25 are such promising approaches. However, SP-GCMs and GCRMs are computationally ex-  
26 pensive and definitely unlikely candidates for operational centers; especially for ensemble  
27 predictions. Nevertheless, the success of these approaches highlighted the importance of  
28 accurate representation of the sub-grid scale (SGS) variability collectively while realizing  
29 the individual behaviour of the convective elements, in the GCMs and their impact on  
30 the large-resolved scales.

31 The most common CCPS are based on the quasi-equilibrium assumption of Arakawa  
32 and Schubert [1974], the moist convective adjustment idea of Manabe *et al.* [1965], or the  
33 large-scale moisture convergence closure of Kuo [1965], and have deterministic closures  
34 which could only represent the ensemble mean, of the SGS convective heating. By adding  
35 stochastic flavour to these deterministic closures encouraging improvements have been  
36 observed [Buizza *et al.*, 2007; Lin and Neelin, 2003]. Majda and Khouider [2002] were the  
37 first to propose a stochastic model for convective inhibition (CIN) that allows both inter-  
38 nal interactions between the convective elements and two-way interactions between the  
39 convective elements and the resolved scale. When coupled to a toy GCM, this stochastic

40 parameterization produced eastward propagating convectively coupled waves that qual-  
41 itatively resemble observations [Khouider *et al.*, 2003]. Plant and Craig [2008] derived  
42 a Poisson distribution for the number of plumes in a convective ensemble conditional  
43 on convective available potential energy (CAPE) and an exponentially distributed cloud  
44 base mass flux based on the theory of equilibrium statistical mechanics. Although not  
45 specifically designed for aggregating convection, its recent implementation in the NCAR  
46 atmospheric community model showed promising success [Wang *et al.*, 2016].

47 The stochastic multicloud model (SMCM) was first introduced in Khouider *et al.* [2010]  
48 to specifically capture the variability due to multi-scale organized convective systems in the  
49 spirit of the superparameterization approach, as a natural extension of the CIN stochastic  
50 model. By design, the stochastic multi-cloud model mimics the life cycle of organized  
51 tropical convective systems and its interaction with the large scales, as it is observed to  
52 involve three cloud types as the building block across multiple scales. It is based on a  
53 lattice particle interaction model for predefined microscopic (sub-grid) sites that make  
54 random transitions from one cloud type to another conditional to the large-scale state. In  
55 return the SMCM provides the cloud area fractions on the form of a Markov chain model  
56 which can be run in parallel with the climate model without any significant computational  
57 overhead. The SMCM was very successfully tested in both reduced-complexity tropical  
58 models and an aquaplanet global atmospheric model [Frenkel *et al.*, 2012, 2013; Deng  
59 *et al.*, 2015, 2016; Ajayamohan *et al.*, 2016] and also validated and calibrated using radar  
60 and large eddy simulation data [Peters *et al.*, 2013; De La Chevrotière *et al.*, 2015]. Here,  
61 we report, for the first time, the results of its implementation in the fully coupled CFSv2

62 model through the use of prescribed vertical profiles of heating and drying obtained from  
63 observations.

64 Comparison with observations show that the improvements in terms of synoptic and  
65 intra-seasonal variability are significant. In particular while CFSv2 exaggerates the intra-  
66 seasonal variance at the expense of the synoptic contribution, CFSSmcm shows a good  
67 balance between the two as in the observations.

## 2. Model Implementation and Setup

68 CFSv2 is the latest version of the NCEP climate forecast system [*Saha et al.*, 2014a].  
69 While elaborate details on the SMCM and its GCM-implementation can be found in  
70 *Khouider et al.* [2010] and *Deng et al.* [2015] in particular, some changes had to be made  
71 to make it compatible with CFSv2. Some details on the implementation of the SMCM  
72 in CFS, using the CFS reanalysis [*Saha et al.*, 2010] climatology background to serve as  
73 a local radiative convective equilibrium (RCE), is given in the supplementary material.  
74 In a nutshell, moisture, temperature and boundary layer height are inputted from CFSv2  
75 to the SMCM module. The convective heating rates for congestus, deep and stratiform  
76 (c/d/s) clouds are parameterized using the deviations of the thermo-dynamical/dynamical  
77 fields obtained from CFSv2, from the prescribed local RCE state. A stochastic lattice of  
78 40x40 convective sites is overlaid over each GCM grid box, so that the sites are only a  
79 few kilometers apart in order to physically represent cloud type and at the same time  
80 capture the right amount of variability [*Frenkel et al.*, 2012]. An order parameter takes  
81 the values 0,1,2,3 at each lattice site according to whether the site is clear sky or occupied  
82 by c/d/s cloud, respectively. A single site transition occurs following a Markov jump

83 stochastic process in the form of a multi-dimensional birth-death process whose transition  
84 probabilities depend explicitly on the large-scale mid-tropospheric dryness (MTD) and  
85 CAPE. The closure is formulated so that the c/d/s heating is proportional to the c/d/s  
86 cloud area fractions in a GCM grid. Deep convection is closed by combining CAPE  
87 and moisture adjustment processes while congestus heating is tied to low-level CAPE.  
88 Stratiform heating follows an adjustment equation towards a fraction of deep convection.  
89 The vertical distribution of heating and drying are based on imposed Q1 and Q2 profiles  
90 [Johnson *et al.*, 2016] carefully derived from reanalysis and TRMM data separately for  
91 each cloud type. In particular, congestus clouds heat the lower troposphere and cool the  
92 upper troposphere, deep convection heat the entire troposphere while stratiform clouds  
93 heat the upper troposphere and cool the lower troposphere. In this fashion the sequence  
94 of congestus, deep then stratiform cloud morphology following the progressive moistening  
95 and then drying of the lower troposphere yields a tilted heating field as it characterizes  
96 multi scale tropical convective systems [Mapes *et al.*, 2006; Khouider and Majda, 2006].  
97 The sub-grid cloud-radiation interactions are not included.

98 The coupled CFS-SMCM model (CFSsmcm) is run for 15 years and the last 10 years  
99 were analyzed in comparison with a similar run using the original CFSv2 model as a control  
100 simulation. The two runs are made at T126 resolution and 10 minutes time step and  
101 validated against precipitation from TRMM3b42-v7 (0.25°x 0.25°; daily) [Huffman *et al.*,  
102 2010], outgoing long-wave radiation (OLR) from NOAA (2.5°x 2.5°; daily) [Liebmann and  
103 Smith, 1996] and the thermo-dynamical and dynamical parameters from NCEP reanalysis  
104 [Kalnay *et al.*, 1996].

### 3. Results and Key Improvements

#### 3.1. The mean state

105 Figure 1 provides an overall idea of the mean state (rainfall in shading and OLR con-  
106 tours) of the model. Precipitation is overestimated in both models, as evident from the  
107 average (over 50°S-50°N) annual mean precipitation shown by the numbers at the right  
108 hand top corners of the panels a-f. While the simulated climatologies look globally sim-  
109 ilar, region wise CFSSmcm shows a few improvements. For example, the dry biases over  
110 the Indian summer monsoon (ISM) region, northern Australia, and Amazonia and the  
111 wet bias over the western (especially during winter) and central-North Pacific have sub-  
112 stantially reduced. Reduction of the wet bias over the equatorial Indian ocean during  
113 boreal summer is crucial as it has serious consequences in capturing interannual rainfall  
114 and sea surface temperature relationship. However some exaggeration in precipitation  
115 is noticeable west of the mountain ranges, namely Congo, Mekong and Andes, along the  
116 western coastlines. Figure S1 (in the supplemental material) provides details of differences  
117 of the simulated seasonal mean rainfall from the observations and the reference model.  
118 Precipitation biases are partly due to bias in local events and partly due to bias in the  
119 location of the inter-tropical convergence zone (ITCZ). Proper simulation of the ITCZ  
120 involves complex air-sea interactions which are beyond convective parameterization. So  
121 the overall annual rainfall mean state looks similar for the two simulations since they  
122 share the same ocean and air-sea interaction models. The double ITCZ problem remains  
123 particularly unresolved. The OLR contours are noted to follow the precipitation pattern.  
124 Noteworthy, in CFSSmcm the radiation feedback in the cloud scale has not been included.  
125 However, in CFSSmcm, like in reality [Houze, 1997], deep clouds decay through stratiform



126 phase. This enables the radiation field sense and respond to the parameterized convective  
127 cloud. The fact that in the SMCM, the timescale of conversion of deep to stratiform is 25  
128 minutes and that of decay of stratiform is 12 hours allows the persistence of a top heavy  
129 heating profile that forces convergence of moisture in the upper troposphere, which in turn  
130 allows the resolved scale micro-physics to produce stratus clouds and indirectly connect  
131 the cumulus parameterization to the radiation scheme and more importantly precipitation  
132 to the OLR field.

133 The boreal summer mean rainfall (in shading) and OLR (contours) is shown in Figure  
134 1d-f. OLR contours are found to match the precipitation pattern closely. The annual-  
135 global-mean value suggests that, overall, CFSsmcm simulates a better OLR field. Indeed,  
136 an overestimation of both OLR and rainfall in CFSv2 simulations is associated with  
137 their biased joint-distribution as demonstrated in Section 3.4 along with the fact that  
138 CFSsmcm shows significant improvement in this regard. In the CFSsmcm climate, the  
139 improvement of OLR field over ISM region and south-east Pacific (off the coast of Peru)  
140 is noteworthy. Especially, in the backdrop of the fact that, a major concern of the CFSv2  
141 simulations is the ISM dry bias [*Saha et al.*, 2014b].

142 One major concern of CFSv2 climate is an unrealistically cold middle troposphere [*Saha*  
143 *et al.*, 2014b] arguably due to the lack of proper stratiform cloud radiative forcing feedback  
144 [*Frenkel et al.*, 2015]. Figures 1g and 1h show the bias in the two simulated (zonally  
145 averaged) temperature fields. Apart from having cold bias in the mid-troposphere, CFSv2  
146 has a warm bias in the top of the troposphere around 200-100hPa. CFSsmcm successfully  
147 gets rid of the warm bias at the top of the troposphere but shows limited ability to reduce

148 the cold bias in the middle troposphere. As a testimony to simulating a better temperature  
149 field, CFSsmcm improves the circulation patterns (Figures not shown).

### 3.2. The variability

150 So far, CFSsmcm simulates a reasonable mean climate which is as good as CFSv2  
151 climate, or better. Noteworthy, CFSv2 is already one of the best state-of-the-art GCMs  
152 [*Sabeerali et al.*, 2013]. Here we further assess CFSsmcm by analyzing the variability of  
153 the simulated climate. First, we examine the share of the synoptic variance (variance  
154 of 2-9 day Lanczos bandpass filtered rainfall anomalies) and the variance in the intra-  
155 seasonal oscillation (ISO) time-scale (variance of 10-90 day Lanczos bandpass filtered  
156 rainfall anomalies) in the total variability, following *Goswami et al.* [2014] who showed  
157 that CFSv2 systematically underestimates the contribution from synoptic variance.

158 Figure 2c reveals, the total boreal summer daily variance is over estimated in CFSsmcm  
159 simulations compared to that of TRMM (Figure 2a). CFSv2 simulations (Figure 2b) look  
160 better compared to CFSsmcm. Overestimation of the total daily variance suggests possible  
161 excessive simulation of extreme rainfall events by CFSsmcm. Which is, in fact, consistent  
162 with the results documented in Section 3.4. Based on our experience during the parameter  
163 tuning of the CFSsmcm, we posit that, a more careful calibration of the parameters  
164 responsible for MTD (though not considered here) would prove beneficial to get rid of  
165 this bias. Comparing Figures 2d & 2e and 2g & 2h, we note that CFSv2 underestimates  
166 (overestimates) the relative contribution of the synoptic (ISO) scale variance. This is  
167 consistent with the results of *Goswami et al.* [2014, 2015]. In the CFSsmcm simulations  
168 (Figures 2f and 2i), the relative contribution of the synoptic and ISO variances towards

169 the total variance resembles much better with the observations. Interestingly, a similar  
170 improvement was seen in the superparameterized version of CFSv2 [*Goswami et al.*, 2015]  
171 as well. The unrealistic simulation of relative contributions of the synoptic and ISO  
172 variances resulting in a reasonable mean (Figure 1b and 1e) indicates the possibility of a  
173 wrong mechanism leading to a right result in CFSv2. This in fact reaffirms the importance  
174 of proper representation of the SGS scale variability in GCMs in order to better simulate  
175 the synoptic and intra-seasonal variability. For Figures 1d-i, it should be kept in mind  
176 that the percentage contributions are most relevant for the qualitative representation of  
177 organized convection dynamics than the total variance itself. The total variances are  
178 shown in see Figure S2.

### 3.3. Equatorial Wave Spectrum

179 Convectively coupled equatorial waves (CCEW) are the carriers of the perturbations  
180 occurring in the tropics. Accurate simulation of these waves is essential to simulate  
181 the climate variability. We carried out a wave number-frequency analysis following the  
182 methodology of *Wheeler and Kiladis* [1999] on OLR field for observation and the two  
183 simulations.

184 CFSv2 shows limited ability in capturing the CCEW spectrum. Apart from having  
185 realistic power in the  $n=1$  equatorial Rossby (ER) waves, CFSv2 either overestimates  
186 or underestimates the CCEWs. The power in the Madden-Julien oscillation (MJO) is  
187 very weak with a slightly longer time-period than observations (Figure 3b). The power  
188 in the westward 3-6 day regime representing the tropical depressions is reasonable in the

189 symmetric spectra of CFSv2 (Figure 3b); however it is overestimated in the antisymmetric  
190 spectra (Figure 3e).

191 Undoubtedly, the CCEW spectrum has improved significantly in CFSsmcm simulations  
192 (Figure 3c and 3f). The improvement of power in the MJO,  $n=-1$  Kelvin,  $n=1$  ER,  $n=1$ ,  
193 2 westward inertia-gravity (WIG) and  $n=0$  mixed rossby-gravity (MRG) compared to the  
194 CFSv2 simulations is truly remarkable. However, CFSsmcm still needs to install some  
195 more power in the significant modes to match with the observations (Figure 3a and 3d).  
196 Also the power in the MJO has faster time periods in CFSsmcm than observations but the  
197 qualitatively improved WK-spectra suggests that CFSsmcm simulates better organization  
198 of convection.

### 3.4. Rainfall and OLR Distribution

199 A reasonable climatological mean rainfall (section 3.1) with a good organization of  
200 convection (section 3.3) suggests an improved simulation of mesoscale convective systems.  
201 This in turn suggests that, the CFSsmcm has an improved distribution of clouds associated  
202 with different rainfall events. Considering OLR as a proxy for cloud tops, we plot in Figure  
203 4, the OLR-rainfall joint probability distribution.

204 In observations (Figures 4a and 4d), for ISM as well as for the entire tropics, we note  
205 OLR values roughly ranging between  $100-300\text{Wm}^{-2}$ . The OLR values are centered about  
206  $200\text{Wm}^{-2}$  for the lowest intensity rainfall events which gets skewed toward relatively lower  
207 OLR values as we climb up the rainfall axis. Noticeably, OLR scatter for heavy rainfall is  
208 more in ISM than over tropics. This possibly is due to the fact that in the ISM climate,  
209 some of the highly rainy days are actually due to incessant rain coming from nimbostratus

210 clouds rather than the result of a deep cumulonimbus convection [*Johnson and Houze,*  
211 1987]. Also a feeble second maximum exists at about ( $270\text{Wm}^{-2}$ ,  $0\text{-}2\text{ mmday}^{-1}$ ); more  
212 prominent for ISM climate. CFSv2 (Figure 4b and 4e) clearly misses to capture the wide  
213 spectrum of clouds over the entire tropics; ISM region being no exception. The majority  
214 of OLR values fall between  $100\text{-}200\text{ Wm}^{-2}$  suggesting an affinity of CFSv2 for high level  
215 clouds. This may be a result of the simplified Arakawa-Schubert (SAS) convective scheme  
216 detraining only through the top of the cloud column resulting in a moist upper atmosphere  
217 and dry middle troposphere [*Pattanaik et al., 2013*]. Improvement is evident in CFSsmcm  
218 simulation in Figure 4c and 4f. The OLR values are spread across a much wider range  
219 compared to CFSv2 simulations, although still narrower than observations, suggesting a  
220 better spectrum of clouds in the CFSsmcm atmosphere. Affinity to produce rain events  
221 with low associated OLR values is significantly reduced in the ISM domain and for the  
222 entire tropics as well. Noteworthy, CFSsmcm could capture the wider spread of OLR  
223 values associated with heavier rainfall events for ISM climate compared to the entire  
224 tropics. This suggests the ability of CFSsmcm to recognize the complexity of the ISM  
225 climate and to distinguish it from the rest of the tropics. The secondary peak at about  
226  $270\text{Wm}^{-2}$  is also captured, although exaggerated. This improved simulation of the rainfall-  
227 cloud association suggests a better simulation of mesoscale complexes in CFSsmcm, which  
228 in turn promises a better organization and variability in the simulated climate.

### 3.5. Organization and Propagation Features

229 The organization of convection over the tropics is relevant only when it propagates in  
230 the right direction. On the intra-seasonal scales, convection is observed to oscillate quasi-

231 periodically with periodicity 30-60 days northward in the ISM region and eastward along  
232 the tropical channel, especially over the warm waters of Indian Ocean and West Pacific  
233 during both boreal summer and winter [*Goswami, 2012*]. In Figure 5 we plotted the lag-  
234 regressed 20-90 day band-pass filtered rainfall and zonal wind at 850hPa. In Figure 5a-c,  
235 the rain and wind fields are averaged for 70°E-90°E and for Figure 5d-i, they are averaged  
236 over 5°S-5°N.

237 In the observations (Figure 5a) the convection starts at the equator and moves to about  
238 20°N with a phase speed of approximately a degree a day. There are two maxima of  
239 convection, one over the warm waters of the equatorial Indian Ocean (EIO) and the  
240 other over the monsoon trough, between 15°N-20°N. The two associated maxima in the  
241 regressed zonal winds suggests the dynamically coupled nature of organized convection.  
242 CFSv2 (Figure 5b) captures this feature reasonably well although the migration is not  
243 as smooth as in observations with a hint of southward movement 2-3 degrees north of  
244 the equator. This southward movement of convection is restricted to the south of the  
245 equator in observations (Figure 5a). Convection over the EIO is overestimated, which  
246 *Goswami et al. [2014]* had attributed to unrealistic air-sea coupling in CFSv2. Moreover,  
247 the inability to simulate the second maximum in the regressed zonal winds raises questions  
248 on CFSv2's ability to simulate the coupled nature of tropical convection. In CFSsmcm  
249 simulation (Figure 5c), the northward propagation of convection is as prominent as in  
250 the CFSv2 and is quantitatively closer to the observed phase speed unlike CFSv2 which  
251 appears to be slower. Like in CFSv2, the southward migration of convection starts from  
252 north of the equator in CFSsmcm as well. In addition, the maximum in convection over

253 Indian Ocean is seen south of the equator at approximately  $5^{\circ}\text{S}$ . However, the tendency to  
254 simulate two maxima for the regressed zonal winds suggest improvement in the circulation  
255 associated with the convection in the CFSsmcm simulated ISM.

256 Figure 5d-f and 5g-i show the eastward propagation of convection during boreal summer  
257 and winter respectively. Clear eastward movement is observed (Fig 5d and 5g) in both  
258 seasons starting from central-EIO to west-central Pacific with a relatively weaker orga-  
259 nization over the Maritime Continent. This is possibly due to the competition between  
260 the strong diurnal cycle of convection and eastward moving organized convection to kill  
261 each other over the Maritime continent [Oh *et al.*, 2013]. Noteworthy, although obvious,  
262 convection over the EIO (west-central Pacific) is relatively stronger (weaker) in the boreal  
263 winter than in summer. In CFSv2 simulations (Figure 5e and 5h), convection weakens  
264 once it reaches Maritime Continent and do not revive passed this barrier, unlike observa-  
265 tions. The relatively stronger convection over the east-EIO in winter than in summer is  
266 captured to some extent. However, in winter the propagation features are simulated even  
267 worse and appear to be almost like a stationary convection over  $90^{\circ}\text{E}$ . In CFSsmcm sim-  
268 ulations (Figure 5f and 5i), the eastward propagation is much better and more prominent  
269 than in CFSv2. The major features, like, the revival of convection passed the Maritime  
270 Continent and the relative strengths of convection in the boreal summer and winter over  
271 the Indian Ocean and the west-central Pacific are reasonably well captured. However the  
272 phase speed appears to be faster than observations and the propagation looks very wobbly.  
273 This wobbliness, although maybe is exaggerated by an excessive stochastic variability, is  
274 arguably due to the chaotic nature of synoptic and mesoscale convective events embedded

275 in the MJO envelope. The propagation of individual synoptic and intra-seasonal events  
276 is also better simulated by CFSsmcm as more intermittent convective systems are seen in  
277 both time and space (results not shown).

#### 4. Conclusion and Discussions

278 The SMCM, which was designed to better represent the unresolved variability associated  
279 with multiscale organized convective systems in GCMs, is implemented in CFSv2. A  
280 first-hand look at the mean state and the variability of the CFSsmcm 10-years climate  
281 is reported here. While the mean state of CFSsmcm is comparable to that of CFSv2,  
282 there are some minor improvements. One of the minor improvements include reduction  
283 of the dry bias in the ISM seasonal rainfall, which is of major importance. The most  
284 significant improvements are noted in the synoptic and intra-seasonal scale. The CCEWs  
285 are better simulated in CFSsmcm. The simulated OLR (read cloud) look more realistic in  
286 CFSsmcm spanning across low-middle-high values like the observations. The organization  
287 of convection and its propagation features are much improved compared to CFSv2. The  
288 model also shows better ability, than CFSv2, to identify and distinguish ISM climate from  
289 the rest of the tropics through simulation of rainfall-OLR relation. All the improvements  
290 shown by CFSsmcm relative to CFSv2 are significant because of two major reasons: first,  
291 CFSv2 is already one of the best available state-of-the-art climate models, and second,  
292 the improvements have come without any extra computational cost than running the  
293 conventional CFSv2 model. This is why CFSsmcm can be considered as a successful  
294 attempt to break the convective parameterization deadlock.



295 During the development of the CFSSmcm model, we noted some interesting behaviour.  
296 The model's overall performance show high sensitivity to the mid tropospheric dryness  
297 (MTD) parameter. The simulation of MJO gets highly affected (as we noticed by plot-  
298 ting WK spectra) by changing MTD. Another parameter affecting MJO simulation is the  
299 lifetime of stratiform clouds. We are planning a few more test runs to study the mod-  
300 els sensitivity to MTD. We believe that the excessive overall variance can be alleviated  
301 through a more careful calibration of the MTD parameter. In particular, a different MTD  
302 value may be used over land and over ocean as convection responds differently over land  
303 and ocean. Noteworthy, realistic simulation of eastward propagating Kelvin waves is a  
304 consistent feature of the model, even in its beta version.

305 We are extending our analyses further to get more insight of CFSSmcm behaviour in  
306 particular and the issue of convective parameterization in general. Primarily we would like  
307 to investigate the simulation of convectively coupled equatorial waves in the CFSSmcm.  
308 Also interactive radiation at the sub-grid scale will be considered following the work of  
309 *Frenkel et al.* [2015]. The fact that SMCM is built on a robust mathematical framework,  
310 makes model improvements more transparent. This, in turn, makes the process of model  
311 development more of an outcome of a systematic analysis then being a serendipity [*Held,*  
312 2005] .

313 **Acknowledgments.** The research of BK is partially funded by a grant from the Gov-  
314 ernment of India through the National Monsoon Mission (NMM) and a discovery grant  
315 from the Canadian Natural and Sciences and Engineering Research Council. BBG is a post  
316 doctoral fellow through BK's NMM grant. TRMM3b42-v7 data is obtained from *http* :

317 [//disc.gsfc.nasa.gov/datacollection/TRMM\\_3B42\\_Daily\\_7.html](http://disc.gsfc.nasa.gov/datacollection/TRMM_3B42_Daily_7.html). NOAA OLR data is  
318 obtained from *ftp* : [//ftp.cdc.noaa.gov/Datasets/interp\\_OLR/olr.day.mean.nc](ftp://ftp.cdc.noaa.gov/Datasets/interp_OLR/olr.day.mean.nc). The  
319 NCEP reanalyses product is obtained from *http* : [//www.esrl.noaa.gov/psd/data/gridded/data.ncep.reana](http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reana)  
320 CFSR data for constructing the background for SMCM is obtained from *http* :  
321 [//rda.ucar.edu/datasets/ds093.2/](http://rda.ucar.edu/datasets/ds093.2/).

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**Figure 1.** Climatological annual mean rainfall (shaded) and OLR (contours) (a)TRMM and NOAA, (b)CFSv2 and (c)CFSsmcm. Climatological boreal summer mean Rainfall (shaded) and OLR (contours) (d)TRMM and NOAA, (e)CFSv2 and (f)CFSsmcm. [OLR contour interval is  $20\text{Wm}^{-2}$ ;  $240\text{Wm}^{-2}$  contour is labeled for reference]. Climatological annual zonal mean temperature bias wrt NCEP reanalysis (g)CFSv2 and (h)CFSsmcm. The global mean annual rainfall values are shown at the right hand top corner of the panels (a) to (c) and the global mean boreal summer OLR values are shown at the right hand top corner of the panels (d) to (f).

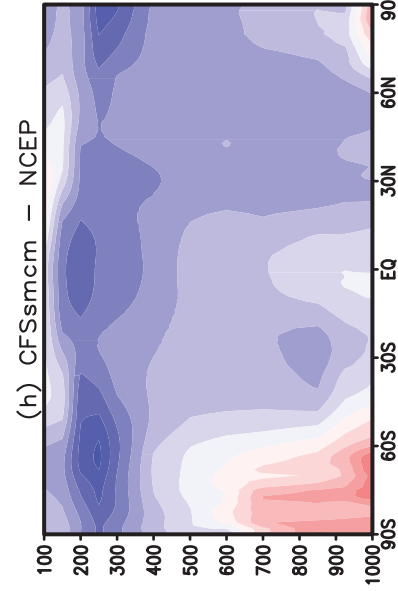
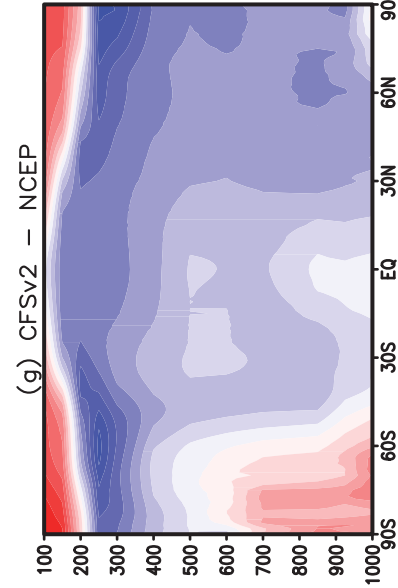
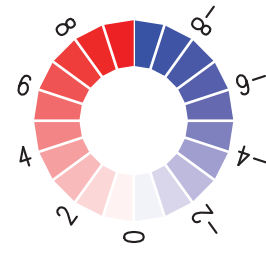
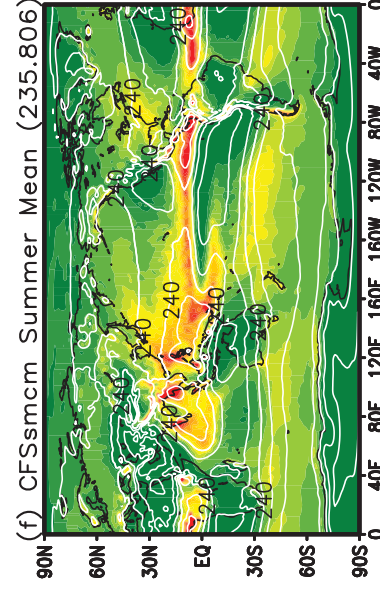
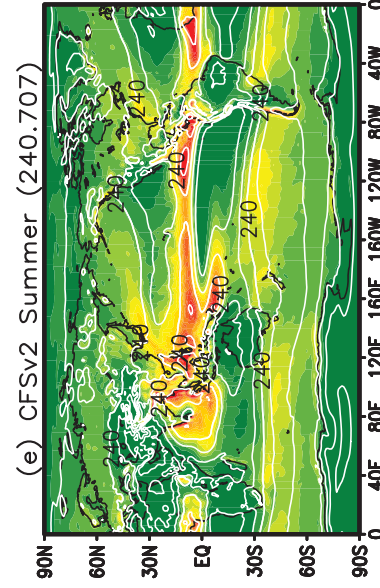
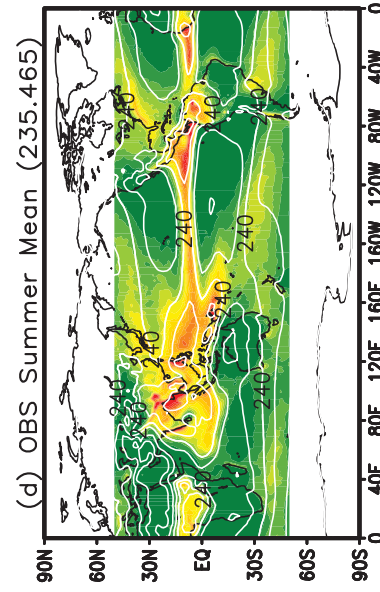
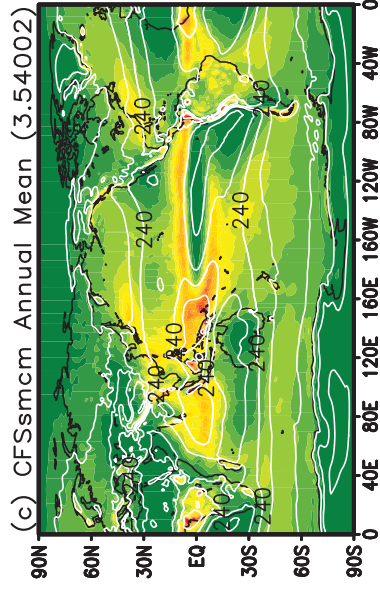
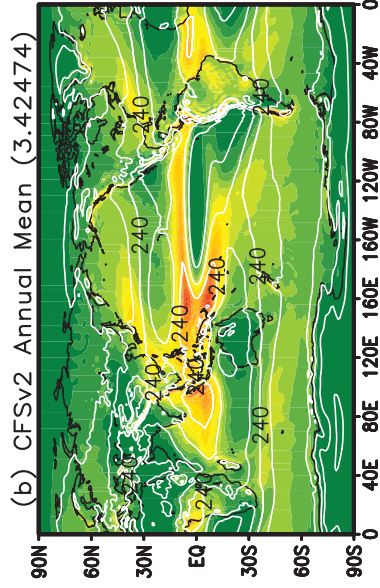
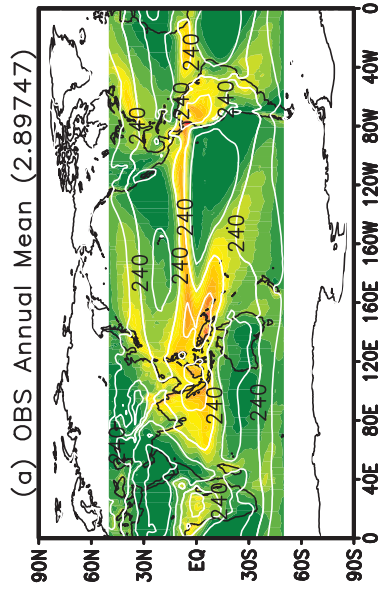
**Figure 2.** Boreal summer total daily rainfall variance ( $\text{mm}^2\text{day}^{-2}$ ) (a)TRMM, (b)CFSv2 and (c)CFSsmcm. Contribution of synoptic variance to the total (d)TRMM, (e)CFSv2 and (f)CFSsmcm. Contribution of ISO variance to the total (g)TRMM, (h)CFSv2 and (i)CFSsmcm.

**Figure 3.** Wheeler-Kiladis spectra of OLR from (a)NOAA, (b)CFSv2 and (c)CFSsmcm, for the symmetric component. The corresponding anti-symmetric spectra are shown in panels d, e and f, respectively.

**Figure 4.** Joint distribution (in %) of OLR-rainfall over ISM region ( $15^{\circ}\text{S}$ - $30^{\circ}\text{N}$ ,  $50^{\circ}\text{E}$ - $110^{\circ}\text{E}$ ), during boreal summer, for (a)Observation (TRMM-NOAA), (b)CFSv2 and (c)CFSsmcm. The corresponding distribution for over entire tropics ( $30^{\circ}\text{S}$ - $30^{\circ}\text{N}$ ) for the whole year is shown in panels d, e and f, respectively. [NOTE: TRMM data is regridded to  $2.5^{\circ}\times 2.5^{\circ}$  resolution to plot this figure.]

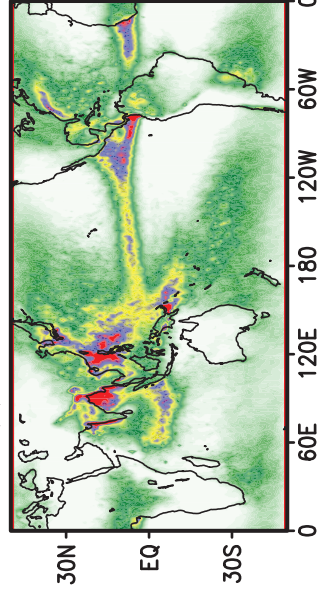
**Figure 5.** Lag-regressed 20-90 day band-pass filtered rainfall (shaded) and zonal wind at 850hPa (contours). In Figure 5a-c, the regressed rain and wind are averaged for  $70^{\circ}\text{E}$ - $90^{\circ}\text{E}$ . For Figure 5d-i, the regressed fields are averaged over  $5^{\circ}\text{S}$ - $5^{\circ}\text{N}$ .

**Figure 1.**

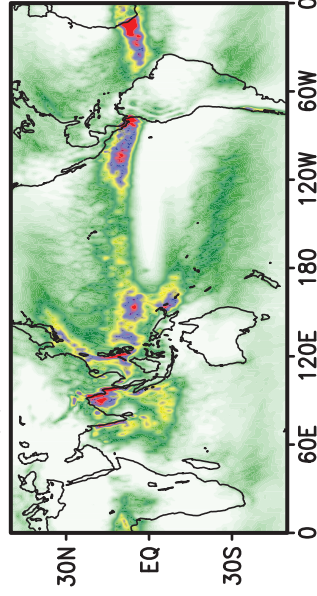


**Figure 2.**

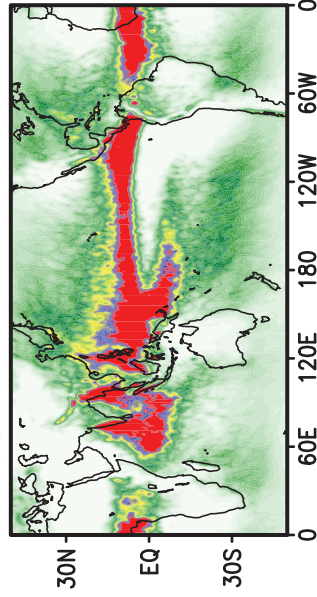
(a) TRMM Total Variance



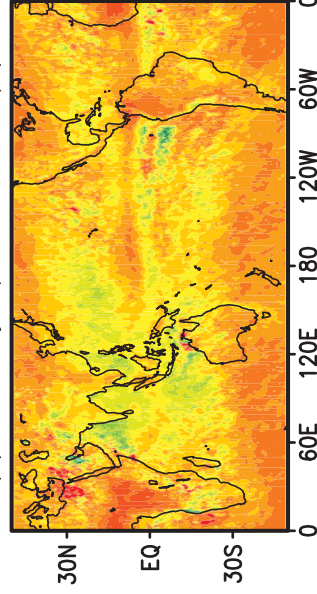
(b) CFSv2 Total Variance



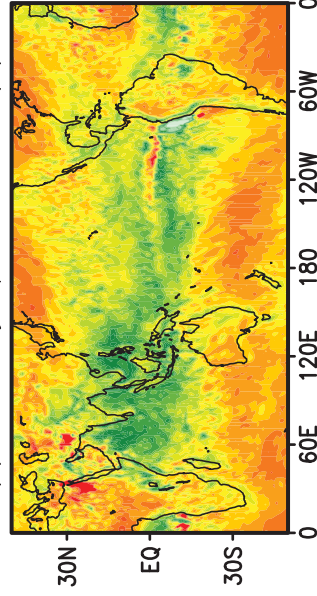
(c) CFSsmcm Total Variance



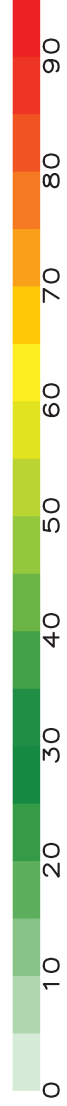
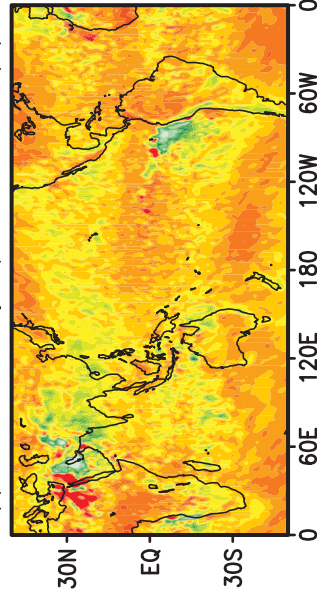
(d) TRMM Synoptic Variance (%)



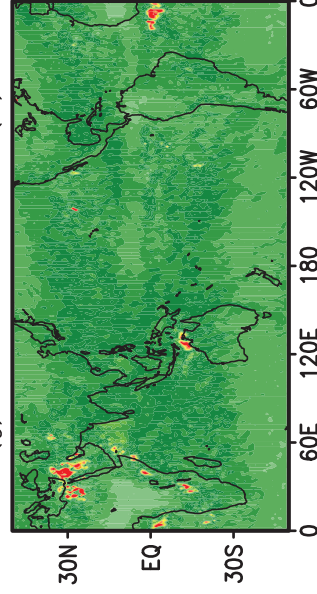
(e) CFSv2 Synoptic Variance (%)



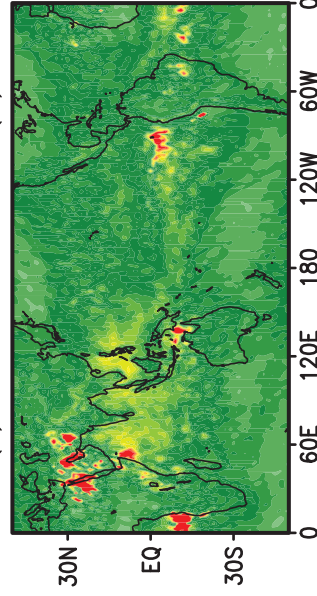
(f) CFSsmcm Synoptic Variance (%)



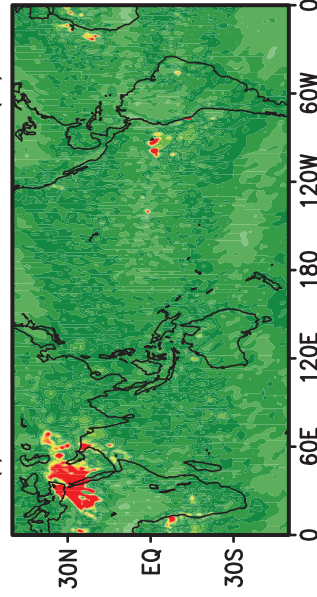
(g) TRMM ISO Variance (%)



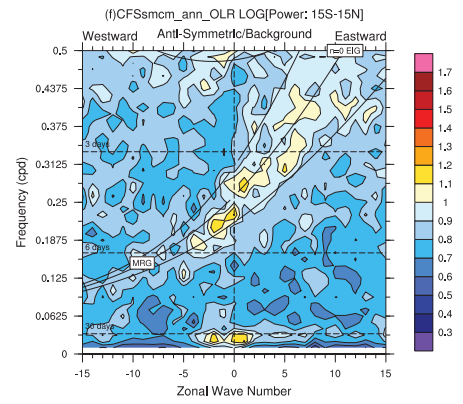
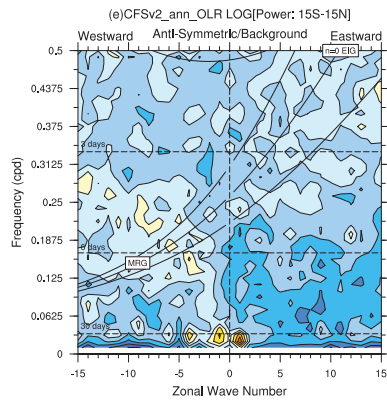
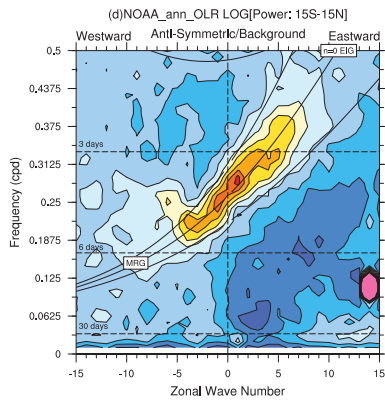
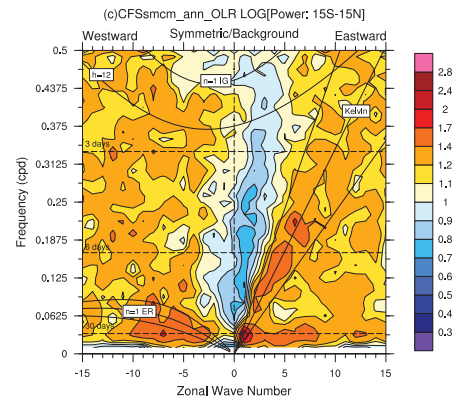
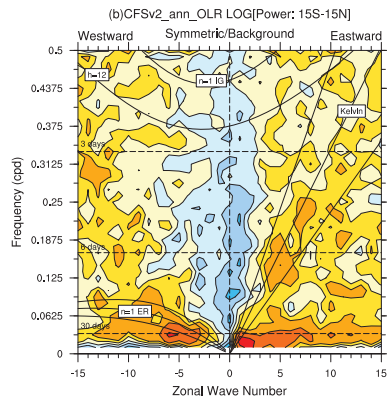
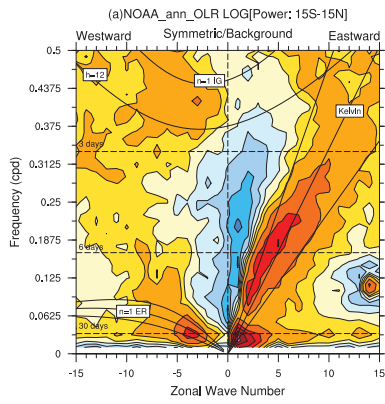
(h) CFSv2 ISO Variance (%)



(i) CFSsmcm ISO Variance (%)

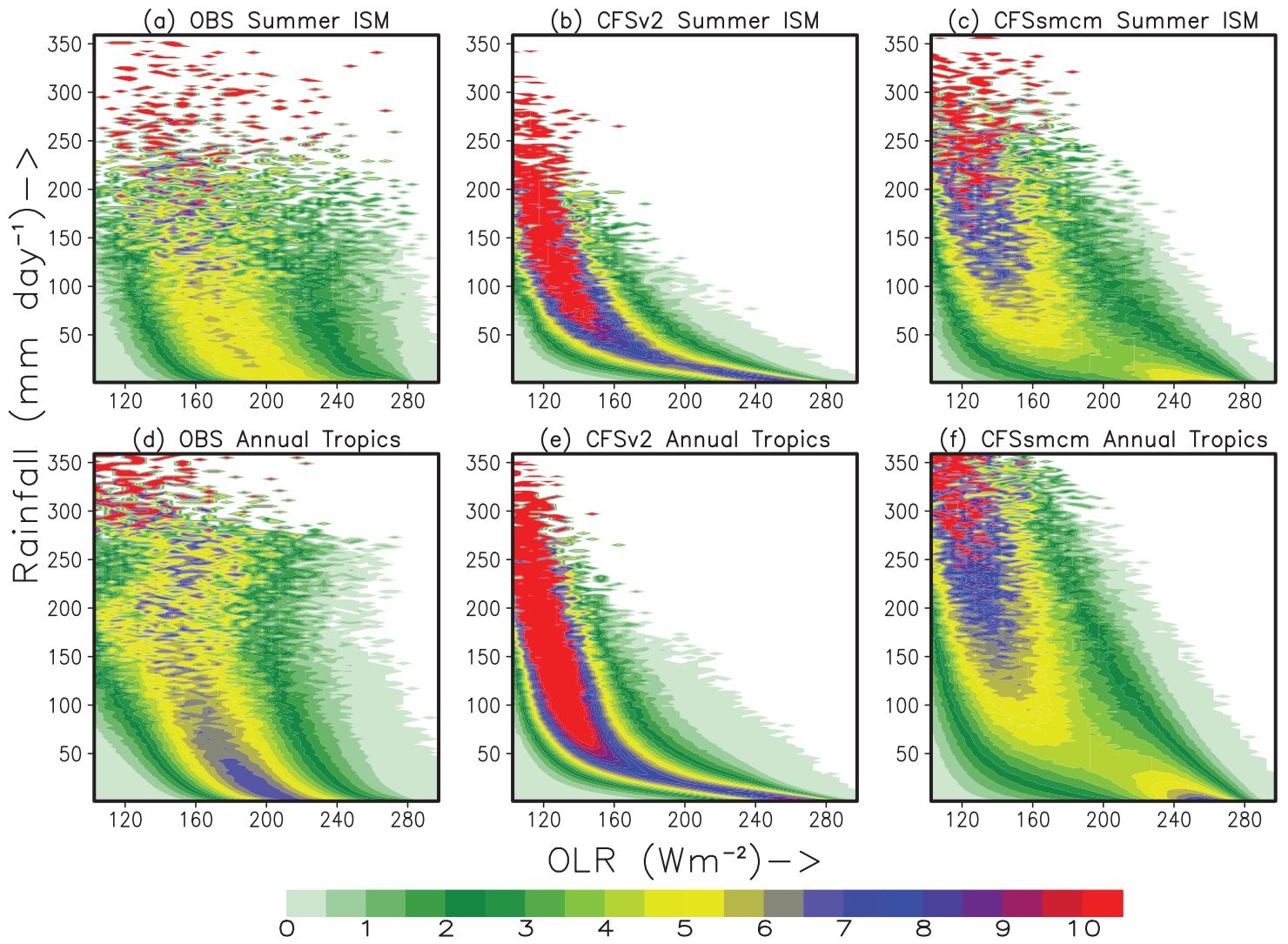


**Figure 3.**





**Figure 4.**



**Figure 5.**

