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► **To cite this version:**

Julien Crétat, Sébastien Masson, Sarah Berthet, Guillaume Samson, Pascal Terray, et al.. Control of shortwave radiation parameterization on tropical climate SST-forced simulation. *Climate Dynamics*, 2016, 47 (5), pp.1807-1826. <10.1007/s00382-015-2934-1>. <hal-01262857>

HAL Id: hal-01262857

<https://hal.sorbonne-universite.fr/hal-01262857v1>

Submitted on 27 Jan 2016

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Control of shortwave radiation parameterization on tropical climate SST-forced simulation

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Submitted to Climate Dynamics

07/30/2015

Revised

10/06/2015

Accepted manuscript – this version is slightly different from the final published version
available at SpringerLink

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33 **Abstract**

34

35 SST-forced tropical-channel simulations are used to quantify the control of shortwave
36 (SW) parameterization on the mean tropical climate compared to other major model settings
37 (convection, boundary layer turbulence, vertical and horizontal resolutions), and to pinpoint
38 the physical mechanisms whereby this control manifests. Analyses focus on the spatial
39 distribution and magnitude of the net SW radiation budget at the surface (SWnet_SFC), latent
40 heat fluxes, and rainfall at the annual timescale. The model skill and sensitivity to the tested
41 settings are quantified relative to observations and using an ensemble approach.

42 Persistent biases include overestimated SWnet_SFC and too intense hydrological cycle.
43 However, model skill is mainly controlled by SW parameterization, especially the magnitude
44 of SWnet_SFC and rainfall and both the spatial distribution and magnitude of latent heat
45 fluxes over ocean. On the other hand, the spatial distribution of continental rainfall
46 (SWnet_SFC) is mainly influenced by convection parameterization and horizontal resolution
47 (boundary layer parameterization and orography).

48 Physical understanding of the control of SW parameterization is addressed by analyzing
49 the thermal structure of the atmosphere and conducting sensitivity experiments to O₃
50 absorption and SW scattering coefficient. SW parameterization shapes the stability of the
51 atmosphere in two different ways according to whether surface is coupled to atmosphere or
52 not, while O₃ absorption has minor effects in our simulations. Over SST-prescribed regions,
53 increasing the amount of SW absorption warms the atmosphere only because surface
54 temperatures are fixed, resulting in increased atmospheric stability. Over land–atmosphere
55 coupled regions, increasing SW absorption warms both atmospheric and surface temperatures,
56 leading to a shift towards a warmer state and a more intense hydrological cycle. This turns in
57 reversal model behavior between land and sea points, with the SW scheme that simulates
58 greatest SW absorption producing the most (less) intense hydrological cycle over land (sea)
59 points. This demonstrates strong limitations for simulating land/sea contrasts in SST-forced
60 simulations.

61

62 **Keywords:** latent heat fluxes – physical parameterizations – radiative budget – rainfall –
63 shortwave radiation schemes – tropical-channel simulations

64 **1. Introduction**

65

66 State-of-the-art global and regional climate models (GCMs and RCMs; see Table 1 for
67 acronyms) used for coordinated projects such as the Climate Model Intercomparison Project
68 Phase 5 (CMIP5) and the Coordinated Regional Downscaling Experiment (CORDEX)
69 struggle in simulating tropical climate. This is evidenced by large model biases and inter-
70 model spread in simulating the radiative budget of the Earth system (e.g., Kothe et al. 2010;
71 Wang and Su 2013; Li et al. 2013; Wild et al. 2013, 2015; Pessacg et al. 2014). The primary
72 atmospheric reason involves difficulty in accounting for sub-grid processes in GCMs and
73 RCMs. Furthermore, the choice of physical parameterizations induces large uncertainties in
74 simulations (e.g., Flaounas et al. 2011; Pohl et al. 2011; Crétat et al. 2012; Hourdin et al.
75 2013; Lim et al. 2015; Raktham et al. 2015), and the physical package performing best at a
76 given resolution does not necessarily perform better at higher resolution (e.g., Wehner et al.
77 2014). While a large body of literature focuses on sensitivity and uncertainties induced by
78 convection (CU), planetary boundary layer (PBL), and microphysics (MP) parameterizations
79 in the tropics, the influence of shortwave (SW) and longwave (LW) radiation
80 parameterizations remains poorly documented.

81 Morcrette et al. (2008) evaluate the effects of radiation parameterization on climate and
82 weather simulated by the Integrated Forecasting System GCM by comparing two radiation
83 packages. The new “McRad” package outperforms the previous radiation package for most
84 parameters and temporal scales, mainly because of improved cloud–radiation interactions.
85 The added value of the McRad package is significant in the tropics due to a better
86 representation in the vertical distribution of diabatic heating.

87 Xu and Small (2002) investigate the influence of two CU and three SW/LW schemes on
88 intraseasonal variability of the North American Monsoon System simulated by the Fifth-
89 Generation Mesoscale Model coupled with the Oregon State University Land Surface Model
90 (LSM). They show that (i) the spread induced by the model physics for simulating rainfall is
91 greater than that induced by model internal variability, (ii) the model skill strongly varies
92 according to the CU – SW/LW combinations, and (iii) radiation schemes including feedbacks
93 between condensation and the water content of clouds perform best.

94 Li et al. (2015) explore the influence of radiation physics on the simulation of the West
95 African Monsoon in the Weather Research and Forecasting (WRF) – Community Land Model
96 framework. Again, radiation schemes significantly modulate the rainfall pattern and
97 associated dynamics, through modifying the meridional thermal gradient between the Sahara

98 desert and the Guinean coastline.

99 These studies highlight tremendous sensitivity of weather and climate to radiation
100 package, but do not assess the control exerted by each of its components (i.e., SW and LW
101 parameterizations) and/or do not discuss the relative influence of radiation parameterizations
102 compared to that of the other physical parameterizations. Pohl et al. (2011) quantify
103 uncertainties in simulating the seasonal mean atmospheric water cycle in equatorial East
104 Africa with the WRF model. They perform sensitivity tests to the model physics (CU, MP,
105 PBL, SW, LW schemes, and LSM), land-use categories, lateral forcing data, and domain
106 geometry. They find that SW parameterization is much more critical than LW
107 parameterization and exerts the largest influence on rainfall, far beyond the influence of CU
108 parameterization. Similar results are obtained for seasonal rainfall in the southwest of
109 Western Australia (Kala et al. 2015), winter rainfall over continental China (Yuan et al.
110 2012), and storms in South-East Australia (Evans et al. 2012).

111 Most of the aforementioned RCM-based studies focus on relatively small target regions,
112 which drastically reduces the degrees of freedom of their model (i.e., the possibility of the
113 model to free oneself from lateral boundary forcing), and thus limits the influence of the
114 model physics (Lucas-Picher et al. 2008; Leduc and Laprise 2009). Furthermore, these studies
115 do not assess the path(s) by which the control of SW parameterization operates, and rarely test
116 all the possible combinations of parameters, only way to properly quantify both the control of
117 each type of parameterization and uncertainties within each type of parameterization. We
118 propose to fill these gaps through analyzing multi-physics and multi-resolution tropical-
119 channel simulations done with the WRF model forced with prescribed sea surface
120 temperatures (SSTs). This model is well suited for sensitivity studies since it incorporates a
121 vast number of different physical parameterizations. Its tropical-channel configuration has
122 been successfully used for studying tropical inertia-gravity waves (Evan et al. 2012), tropical
123 tropopause (Evan et al. 2013), the Madden-Julian Oscillation (Ray et al. 2011; Ulate et al.
124 2015), and downscaling strategies (Hagos et al. 2013), but never for quantifying uncertainties
125 in simulating tropical climate.

126 The purpose of this study is threefold: (i) assess the model skill in capturing key
127 parameters of the energy budget and atmospheric water cycle and how this skill is sensitive to
128 the model physics (SW, CU, PBL parameterizations), vertical and horizontal resolutions (VR
129 and HR, respectively); (ii) quantify the control of SW parameterization on tropical climate
130 and model skill relative to that of the other settings; (iii) investigate the physical mechanisms
131 by which this control operates. Simulated SWnet_SFC, latent heat fluxes, and rainfall are

132 analyzed at the annual timescale and evaluated against satellite-based observations.

133 Section 2 presents the tropical-channel simulations, the satellite-based observations, and
134 how confidence is evaluated. Section 3 quantifies the control SW parameterization has on the
135 model skill relative to that of the other settings, and identifies persistent model deficiencies
136 across the parameters tested. Section 4 investigates how SW parameterization controls
137 tropical climate simulation. Section 5 briefly discusses the respective influence of SW and CU
138 parameterizations on tropical rainfall. Conclusions are provided in Section 6.

139

140

141 **2. Experimental setup, data, and confidence**

142

143 2.1 Tropical-channel atmospheric simulations

144

145 Four sets of tropical-channel simulations (Table 2) with prescribed SSTs are run using
146 the Advanced Research WRF model (Skamarock et al. 2008) V3.3.1, with lateral boundaries
147 placed at 46° and the top of the atmosphere set at 50 hPa. All simulations are constrained by
148 the 6-hourly $3/4^\circ \times 3/4^\circ$ ERA-Interim reanalysis (ERA-I; Dee et al. 2011) and version 2 of the
149 $1/4^\circ \times 1/4^\circ$ daily optimum interpolation SST analysis from NOAA (Reynolds et al. 2007), and
150 are initialized on 00Z 1 January 1989.

151 Settings that are the same for the first three sets of simulations include Betts-Miller-
152 Janjic CU scheme (BMJ; Betts and Miller 1986, Janjic 1994), WSM6 MP scheme (Hong and
153 Lim 2006), LW Rapid Radiative Transfer Model (RRTM; Mlawer et al. 1997), Monin-
154 Obukhov surface layer, and the unified Noah LSM with surface characteristics from the
155 MODIS 20-category land-cover classification (Chen and Dudhia 2001).

156 Set #1 (Table 2) consists of 16 10-year long simulations (1989 – 1998 period)
157 performed to (i) identify persistent biases whatever the settings tested, (ii) quantifying the
158 control exerted by SW parameterization on the annual mean climatology of tropical climate,
159 and (iii) testing the sensitivity of the results to different model settings. The 16 simulations
160 correspond to all possible combinations between 2 SW schemes, 2 PBL schemes, 2 VR and 2
161 HR refinements.

162 The two SW schemes selected are the Dudhia (Dudhia 1989) and Goddard (Chou and
163 Suarez 1999) schemes. They are widely used for both weather forecasts and climate
164 simulations, and perform best among extensive sensitivity tests achieved during the early
165 stage of this work (not shown). The Dudhia scheme is a simple broadband downward

166 integration that accounts for water vapor and cloud absorption, cloud albedo, and clear-air
167 scattering. The percentage of solar irradiance scattered in a model layer is directly
168 proportional to the layer-integrated density of the dry air and a bulk scattering coefficient. The
169 latter summarizes all scattering and absorption (aerosol and Rayleigh scattering, stratospheric
170 ozone and aerosol absorption) processes not explicitly included in the scheme, and its default
171 value ($10^{-5} \text{ m}^{-2} \text{ kg}^{-1}$) is derived from atmospheric conditions observed during the First
172 International Satellite Land Surface Climatology Project Field Experiment (Zamora et al.
173 2005). The Goddard scheme accounts for the rapidly varying shortwave flux with
174 wavenumber by integrating solar flux into 11 spectral bands spanning from 0.175 to 10 μm ,
175 and extinction by water vapor, ozone, oxygen, carbon dioxide, aerosols, Rayleigh scattering,
176 and clouds. Layer reflections and transmissions are computed using the δ -Eddington
177 approximation (Joseph et al. 1976). Its accuracy is expected to be within a few $\text{W}\cdot\text{m}^{-2}$ whereas
178 the atmospheric heating rate between 0.01 hPa and the surface is accurate to within 5%
179 relative to line-by-line calculations (Chou and Suarez 1999). The comparison of the simple
180 Dudhia scheme with a more classical SW scheme such as the Goddard allows physical
181 understanding on the role of SW absorption over various regions.

182 The remaining settings, varying between the 16 simulations, include the non-local
183 Yonsei University (YSU; Hong et al. 2006) and turbulent kinetic energy Mellor-Yamada-
184 Nakanishi-Niino (MYNN; Mellor and Yamada 1982, Janjic 2002, Nakanishi and Niino 2004)
185 PBL schemes, 45 and 60 layers (L45 and L60 hereafter) VR, and $3/4^\circ$ and $1/4^\circ$ HR. The L45
186 is the standard WRF configuration, and the L60 configuration has 3 times more levels below
187 800 hPa.

188 To assess the robust effect of each model setting, two 8-member ensembles per model
189 setting are selected from Set #1. For instance, the two SW ensembles differ only from the SW
190 scheme used and their 8 members are combinations between the 2 PBL schemes, the 2 VR
191 and the 2 HR refinements tested. The control of SW parameterization is given by the spread
192 within each of the two SW ensembles (i.e., inter-member spread) relative to the spread within
193 each of the two PBL, VR, and HR ensembles. A strong control of SW parameterization
194 corresponds to weaker inter-member spread within the two SW ensembles than within the two
195 PBL, VR, and HR ensembles, i.e. when the control is reproducible under different SW
196 schemes. On the other hand, the difference between the two SW ensemble means measures
197 the sensitivity to the way SW radiations are parameterized. The same methodology is applied
198 to the other settings.

199 Sets #2 to #4 consist of 1-yr long simulations run for the year 1989 (Table 2). Set #2 is
200 the same as Set #1 but with 3/4° HR and L60 VR. It helps understanding model biases by
201 archiving additional diagnostics (see Table 2). Set #3 is used for understanding the processes
202 explaining differences between the two SW schemes, with an emphasis on their main
203 differences: explicit O₃ absorption in the Goddard scheme and the scattering coefficient in the
204 Dudhia scheme. This is achieved by running and analyzing one Goddard simulation set
205 without O₃ absorption, and 11 Dudhia simulations with the scattering coefficient varying from
206 $2 \times 10^{-5} \text{ m}^{-2} \text{ kg}^{-1}$ to 0 every $0.2 \times 10^{-5} \text{ m}^{-2} \text{ kg}^{-1}$. All simulations from Set #3 use the YSU PBL
207 scheme, L60 VR, and 3/4° HR, a good compromise between model skill and computer
208 resources. Set #4 aims at discussing the relative weight CU and SW parameterizations have
209 on tropical rainfall simulation. It is similar to the 8 3/4° HR simulations from Set #1 but with
210 the Kain-Fritsch (KF; Kain 2004) mass-flux instead of the BMJ adjustment-type CU scheme.

211

212 2.2 Observations

213

214 The model skill in simulating SWnet_SFC, latent heat fluxes, and rainfall is assessed
215 against the annual mean climatology of different satellite-based datasets.

216 The annual climatology of SWnet_SFC is derived from the Cloud and Earth's Radiant
217 Energy System (CERES) Energy Balanced and Filled (EBAF edition 2.8) data over the 2000
218 – 2013 period. Commonly used for model output evaluation (e.g., Hourdin et al. 2013), the
219 CERES-EBAF data include monthly mean radiation fluxes at the surface and the top of the
220 atmosphere under full- and clear-sky conditions at a 1° spatial resolution. They are produced
221 by deriving the energy balance from AQUA, TERRA and geostationary satellites, and
222 adjusting it to that inferred by Loeb et al. (2012) from the measured warming of the oceans. A
223 complete description of the data is available in the CERES website
224 (<http://ceres.larc.nasa.gov>).

225 The Objectively Analysed air-sea Heat Fluxes version 3 dataset (OAFlux; Yu et al.
226 2008) is used for the annual climatology (1989 – 1998) of latent heat fluxes over ocean. These
227 estimates result from a state-of-the-art flux parameterization applied to an optimal blending of
228 surface meteorological parameters from satellite estimations, numerical weather predictions,
229 and in situ measurements. They are available at the monthly timescale on a 1° x 1° grid from
230 1998 onwards.

231 The NASA 3B42-V7 Tropical Rainfall Measuring Mission (TRMM; Huffman et al.
232 2007; Huffman and Bolvin 2013) is used for rainfall and its annual mean climatology is

233 computed for the 1998 – 2007 period. This product provides 3-hourly estimates at a spatial
234 resolution of $1/4^\circ$ from 1998 to present.

235 Different thermo-dynamic parameters are also analyzed to understand model
236 deficiencies. We choose the ERA-I reanalysis, which is used to constrain all tropical-channel
237 simulations. ERA-I incorporates many improvements in model physics and analysis
238 methodology compared to the previous reanalyses. Included are a new 4D-var assimilation
239 scheme, higher horizontal resolution, a better formulation of background error constraint,
240 additional cloud parameters and humidity analysis, and more data quality control and bias
241 correction.

242

243 2.3 Confidence

244

245 All simulations from Set #1 spin up within a few weeks in terms of energy budget and
246 atmospheric water cycle, except latent heat fluxes over land points that require one year to
247 spin up due to the low-frequency soil moisture adjustment. These simulations also slightly
248 drift towards a more intense hydrological cycle over the 1989 – 1998 period, which reduces
249 the amount of incident SW radiations at the surface through increase in water vapor
250 absorption and stratiform cloud reflection. To ensure the robustness of our results to model
251 spin-up and drift, we analyzed the model skill in simulating annual mean SWnet_SFC, latent
252 heat fluxes and rainfall for each year over the 1989 – 1998 period compared to the observed
253 annual mean climatology. Both the model skill and sensitivity to the settings are similar over
254 the years, motivating to present only results for the annual mean climatology in section 3.

255 We also verified that our results do not differ when (i) moving the temporal windows
256 used for computing the observed annual climatology, and (ii) using different observational
257 datasets (SWnet_SFC from the International Satellite Cloud Climatology Project:
258 <http://isccp.giss.nasa.gov/projects/flux.html>; latent heat fluxes from the TropFlux data:
259 Praveen Kumar et al. 2012; rainfall from version 2.2 of the Global Precipitation Climatology
260 Project: <http://www.esrl.noaa.gov/psd/data/gridded/data.gpcp.html>). Model biases are only
261 weakly sensitive to the period and datasets used. In other words, model errors are much larger
262 than uncertainties related to observations.

263 The spatio-temporal scales analyzed in this study range from annual means at the grid
264 point scale to daily means integrated either temporally (over the year) or spatially (over
265 all/sea/land points within the tropical-channel domain), or both. These scales drastically
266 reduce noise associated with model internal variability (Cr tat et al. 2011), which would not

267 be the case for high-frequency variability at the grid point scale. These caveats taken together
268 with the strong year-to-year reproducibility of our results clearly indicate that the model
269 internal variability is weak for the scales analyzed in our SST-forced simulations.

270

271

272 **3. Model evaluation: common strengths and weaknesses**

273

274 The model performance in representing the net SW radiation budget at the surface
275 (Figure 1), latent heat fluxes (Figure 3) and rainfall (Figure 5) is summarized by using box-
276 and-whisker plots of linear correlation coefficients between observed and simulated spatial
277 distributions and the model root mean square errors.

278

279 3.1 Net SW radiation budget at the surface

280

281 Figure 1a shows the annual mean climatology of SWnet_SFC under full-sky conditions
282 for the CERES-EBAF data. Maxima ($>250 \text{ W.m}^{-2}$) are found in the tropics over oceanic
283 regions where cloud cover is weak. SWnet_SFC decreases both poleward due to the earth
284 rotundity and equatorward due to the presence of deep convective clouds within the inter-
285 tropical convergence zone (ITCZ). Large land/sea and meridian contrasts are also apparent
286 due to larger albedo values over land and the presence of stratocumulus clouds over upwelling
287 regions (e.g., Chile-Peru coast) and the south and east of China (Woods 2012), respectively.
288 The two SW ensemble means struggle in capturing the observed spatial structure (Figs. 1b-c).

289 Figure 1d shows the spatial correlation (r) in the annual mean climatology of
290 SWnet_SFC between the 16 simulations from Set #1 and the CERES-EBAF data. The spatial
291 distribution depicted by the two SW ensemble means weakly differs one another, and the
292 inter-member spread is high, pinpointing that SW parameterization does not drive the spatial
293 distribution of SWnet_SFC.

294 For comparison, the remaining box-and-whisker plots show the inter-member spread
295 within the two PBL, VR, and HR ensembles. The spatial distribution of SWnet_SFC is both
296 more controlled by and sensitive to PBL parameterization and HR than to SW
297 parameterization and VR. The mapping of differences between the two PBL or the two HR
298 ensemble means points out low-level marine cloud regions, especially along and off the
299 Chile-Peru coast (not shown). Moreover, the wide stretching of most box-and-whiskers in
300 Fig. 1d suggests that the model skill in capturing the spatial distribution of SWnet_SFC

301 depends more likely on combined effects of several parameters than on one particular
302 parameter. In this regard and for the metric analyzed in Fig. 1b, simulations combining either
303 the Dudhia or Goddard SW scheme with the YSU PBL scheme with L60 VR and 1/4° HR
304 largely outperform the others (not shown).

305 Figure 1e is the same as Fig. 1d but for the model root mean square errors (RMSE). The
306 spread within each SW ensemble is excessively weak compared to that found in the remaining
307 ensembles, reflecting a strong control of SW parameterization on the magnitude of
308 SWnet_SFC. Furthermore, great differences are found between the two SW ensemble means,
309 while the remaining ensemble means are almost the same. This traduces strong sensitivity of
310 SWnet_SFC magnitude to the SW scheme used, with RMSE value of $\sim 15 \text{ W.m}^{-2}$ and ~ 27
311 W.m^{-2} for the Dudhia and Goddard SW ensemble means, respectively. The origins of these
312 differences are examined in more depth in section 4.

313 Despite magnitude differences, the two SW ensemble means display similar errors
314 spatially (Figs. 2a-b). First, they overestimate SWnet_SFC over convective areas (e.g., ITCZ,
315 South Pacific Convergence Zone, monsoon regions) due to underestimated cloud radiative
316 effects (Figs. 2c-d). This bias is shared by the 16 simulations (not shown) and is related to the
317 absence of convective clouds in the BMJ CU scheme, which produces rainfall by adjusting
318 vertical profiles of moisture and temperature to observed profiles. The non-convective clouds
319 (resolved by the microphysics scheme) are therefore the only one existing in the model and
320 interacting with the SW and LW schemes. CMIP3 and CMIP5 GCMs display similar biases
321 (see, e.g., Fig. 5 in Li et al. 2013), because most of them struggle in representing cloud-
322 radiation interactions (Li et al. 2014). Second, SWnet_SFC is overestimated (underestimated)
323 along (off) the coastal upwelling regions (Fig. 2), especially in the Chile-Peru region. This
324 dipole indicates a westward shift in the location of simulated low-level marine clouds, a bias
325 sharply reduced when moving from 3/4° to 1/4° HR whatever the SW scheme used (not
326 shown).

327 328 3.2 Latent heat fluxes

329
330 Figure 3a shows the annual mean climatology of latent heat fluxes for the OAFlux data.
331 The main sources of latent heat fluxes are located over western boundaries currents (>200
332 W.m^{-2}), tropical and subtropical oceans (up to $120\text{-}160 \text{ W.m}^{-2}$ in the Indian/Pacific and
333 Atlantic).

334 The spatial distribution and magnitude of latent heat fluxes over sea points are largely

335 controlled by SW parameterization, while the remaining model settings have no impact (Figs
336 3b-c). The model skill significantly depends on the SW scheme used with Goddard SW
337 simulations being more in line with the OAFflux data. Latent heat flux biases remain,
338 however, large whatever the SW scheme, with RMSE of 43 (32) $\text{W}\cdot\text{m}^{-2}$ for the Dudhia
339 (Goddard) SW ensemble mean. Spatially, the SW ensemble means systematically
340 overestimate latent heat fluxes over oceans (Figs. 4a-b). In the northern hemisphere, biases
341 increase westward in the Atlantic and Pacific Oceans and are the largest in the China Sea and
342 northern Indian Ocean. In the southern hemisphere, the main positive biases are located
343 equatorward of the Tropic of Capricorn in the three oceans.

344 These overestimations do not result from too intense surface winds simulated by the
345 model since their speeds are underestimated (Figs. 4c-d), but they are consistent with biases in
346 2m specific humidity (Figs. 4e-f), with $r \sim -0.78$ and -0.6 between the two parameters for the
347 Dudhia and Goddard SW ensemble means, respectively. This indicates that positive biases in
348 latent heat fluxes over the oceans at least partly result from overestimated moisture gradients
349 between the surface and the lower atmosphere.

350

351 3.3 Rainfall

352

353 Figure 5a shows the annual mean climatology of rainfall for the TRMM data. Largest
354 rainfall amounts occur in convergence zones of each oceanic basin and over western
355 boundary currents (Kuroshio and Gulf Stream).

356 The 16 simulations from Set #1 accurately capture the observed spatial distribution (Fig.
357 5b: $r > 0.75$), and the inter-simulation spread is relatively weak (greatest r value ~ 0.85). This
358 support the idea that the settings tested in this study do not significantly drive the large-scale
359 distribution of rainfall, the latter being more influenced by prescribed SSTs and CU
360 parameterization as expected from the literature (see section 5). Similar results are found for
361 biases (Figs. 5c), with RMSE ranging between 1.4 and 2 $\text{mm}\cdot\text{day}^{-1}$.

362 The results are much more contrasted when disentangling sea and land points (Figs. 5d-
363 g). First, model errors and inter-member spread are larger over land than sea points, an
364 expected result since the WRF model is forced by observed SSTs over seas while coupled
365 with a LSM elsewhere. One important exception is weaker inter-member spread in the spatial
366 distribution of rainfall simulated over land by the two HR ensembles, due to the strong control
367 exerted by the orography (Fig. 5f). Second, the differences in rainfall biases found between
368 the two SW (or HR) ensembles are clearly reversed over sea and land points. Both the Dudhia

369 SW and 1/4° HR ensembles produce more (less) biases over sea (land) points than the
370 Goddard SW and 3/4° HR ensembles (Figs. 5e and g). The weak differences found between
371 the two SW / HR ensembles at the tropical-channel scale (Fig. 5c) hide thus large spatial
372 differences (Figs. 6a-b), with, e.g., large (moderate) wet biases over the tropical Indian Ocean
373 and China Sea, and dry (wet) biases over South America and Southeast Asia in the Dudhia
374 (Goddard) SW ensemble mean.

375 Despite regional differences, some large-scale errors are obviously shared by the two
376 SW ensemble means. These errors include prominently a 2-3 mm.day⁻¹ dry bias over the
377 Indian subcontinent and a 4-6 mm.day⁻¹ wet bias over the Pacific ITCZ. The wet bias is not
378 reminiscent of the classical double-ITCZ problem (Lin 2007; Oueslati and Bellon 2015) and
379 is partly related to too strong moisture convergence in the two SW ensemble means (Figs. 6c-
380 d). Biases of similar magnitude are also found within a zonal band stretching from the Bay of
381 Bengal to far off the Philippine east coast in line with underestimated summer monsoon flux
382 (Samson et al. 2015) and consistent with latent heat flux and moisture convergence biases
383 (Figs. 4a-b and 6c-d, respectively).

384

385 In summary, the model skill significantly varies according to the model settings, but
386 common weaknesses persist whatever the model physics and resolution, especially the
387 underestimation of cloud radiative effects over convective regions, and huge biases in latent
388 heat fluxes. SW parameterization significantly influences tropical climate simulation, with
389 large repercussions on the radiative budget itself, but also the energy budget and water cycle.
390 The weight of SW parameterization relative to that of CU parameterization will be assessed in
391 section 5.

392

393

394 **4. Sensitivity to SW schemes**

395

396 Section 4 diagnostics the differences between the two SW schemes, and addresses their
397 causes.

398

399 **4.1 Quantifying the differences induced by the two SW schemes**

400

401 Figure 7 shows annual mean climatology differences between the Dudhia and Goddard
402 ensemble means from Set #1. SWnet_SFC is systematically greater in the Goddard than the

403 Dudhia SW ensemble mean (Fig. 7a). The largest differences occur in the western Pacific and
404 Atlantic Oceans, the South Pacific Convergence Zone (30-40 $W.m^{-2}$ in both regions), and in
405 the tropical Indian Ocean (30-36 $W.m^{-2}$). Small differences (0-14 $W.m^{-2}$) are located inland
406 where convection is deep during summer or year-round (i.e., tropical Africa, maritime
407 continent, southeast Asia, and Amazon basin), and in low-level marine cloud regions where
408 the Goddard SW scheme produces more low-level clouds (explicitly resolved by the model)
409 than the Dudhia (see discussion of the Figure 9c), hence less downward SW at the surface.

410 There is significant spatial anti-correlation between differences in SWnet_SFC (Fig. 7a)
411 and in rainfall (Fig. 7b), with $r \sim -0.54$. This indicates that differences in SWnet_SFC decrease
412 where rainfall amounts are larger in the Goddard than the Dudhia SW ensemble mean, and
413 reversely. This involves the effects of stratiform clouds (e.g., anvil clouds resolved by the
414 microphysics) that develop above convective regions (see Figs. 10c-d), consistent with strong
415 positive relationship between convective and stratiform rainfall in our simulations (not
416 shown). The Goddard SW simulates more rainfall over land than the Dudhia SW ensemble,
417 whereas it is the opposite over maritime convective regions, except in the western equatorial
418 Pacific. Over land, differences in rainfall are mainly related to differences in latent heat
419 fluxes. The Goddard produces warmer surface temperatures than the Dudhia SW scheme in
420 response to larger SWnet_SFC. This favors more evaporation, increases the moist static
421 energy below the cloud base and, finally, produces more rainfall. Over sea, where SSTs are
422 prescribed, enhanced rainfall over maritime convective regions in the Dudhia SW ensemble is
423 predominantly associated with higher latent heat fluxes and moisture convergence as
424 demonstrated by the striking similarities between the different patterns (Figs. 7b-d).

425 Since SW parameterization has direct effects on the thermal structure of the atmosphere,
426 we focus on the thermal stability of the atmosphere to understand the mechanisms by which
427 SW parameterization controls tropical climate simulation. Figures 8a-b show the zonal mean
428 in the annual mean climatology of potential temperature (θ) averaged over sea points for the
429 Goddard SW ensemble mean from Set #1 and the differences between the two SW ensemble
430 means, respectively. The focus is given to sea points to avoid mixing SST-prescribed and
431 coupled land-atmosphere regions for which differences between the two SW schemes are
432 reversed (Fig. 7). Note, however, that zonal averaging applied to all grid points within the
433 tropical-channel domain leads to similar results since sea points represent 75% of the total. As
434 expected, the strong vertical gradient of θ observed at mid-latitudes turns weak in the tropics
435 (Fig. 8a). However, the Goddard SW ensemble mean simulates a more stable tropical
436 atmosphere with warmer θ as pressure decreases (Fig. 8b). This is in accordance with weaker

437 updraft (Figs. 8c-d) and lower high-level stratiform clouds (Figs. 8e-f) simulated on either
438 side of the equator by the Goddard simulations. Finally, differences in rainfall (Fig. 7b),
439 vertical velocity (Fig. 8d), and stratiform clouds (Fig. 8f) traduce a thinner marine ITCZ in the
440 meridional direction when using the Goddard SW scheme.

441 To understand land/sea contrasts shown in Fig. 7, Figure 9 shows differences in the
442 vertical profile of θ between the two SW ensemble means over both sea and land points. The
443 effects SW parameterization has on atmospheric stability depend on whether surface is
444 coupled to atmosphere or not. Over sea points where SSTs do not respond to changes in
445 radiations, the atmosphere is more stable in the Goddard than the Dudhia SW ensemble mean,
446 with differences being almost null at the surface because θ is constrained to adjust to
447 prescribed SSTs and increasing with height. Over land points, the use of a LSM allows
448 surface temperatures to respond to changes in radiations, as measured by large spread in the
449 Dudhia – Goddard differences at the surface. These differences are almost uniform between
450 the near surface and ~500 hPa (in the 1.2-1.4 K range), indicating a shift towards a warmer
451 state in the Goddard SW ensemble mean. This induces weaker surface pressure and higher
452 moist static energy simulated by the Goddard than the Dudhia SW scheme (not shown), hence
453 conditions more favorable for convection to develop.

454

455 4.2 Understanding the differences induced by the two SW schemes

456

457 To quantify which components of the model physics explain the differences in the
458 vertical profile of θ seen in Figure 9, we extracted the physics tendencies of θ in the Goddard
459 simulation with O_3 absorption and the Dudhia simulation with the default scattering
460 coefficient from Set #2. These two simulations are defined as control simulations in the
461 following. The tendencies are computed online to avoid aliasing effect, and are extracted
462 using a cumulative averaging methodology.

463 Figures 10a-e show the zonal mean in θ tendencies for the Goddard control simulation
464 over sea points. As expected, 4 out of the 5 terms warm the atmosphere. SW radiations warm
465 the whole atmosphere through gas absorption (e.g., water vapor, CO_2 , O_3) (Fig. 10a), CU and
466 MP processes warm the low- and mid-troposphere by releasing latent heat fluxes (Figs. 10c-
467 d), and PBL turbulence warms the low-troposphere (below 950 hPa) by vertical diffusion
468 (Fig. 10e). Most of these warming effects are counter-balanced by the strong cooling effect of
469 LW radiations in the whole atmosphere (Fig. 10b) and, to a lesser extent, of low-tropospheric
470 cloud and rainfall evaporation induced by MP processes (Fig. 10d). Horizontal diffusion has

471 no significant effect (not shown).

472 Differences in θ tendencies between the two control simulations (Figs. 10f-j) are
473 important for the 5 terms, demonstrating that SW schemes affect climate simulation through
474 interactions with all components of the model physics. We illustrate this point by focusing on
475 differences in deep and shallow convections induced by SW schemes. In the tropics, negative
476 differences in θ tendencies due to CU and MP found between 950 and 300 hPa (Figs. 10h-i)
477 suggest that deep maritime convection is less intense and thinner in the meridional direction
478 in the Goddard than the Dudhia control simulation, consistent with Figs. 7b and 8d. On the
479 other hand, positive differences at 15°S and 15°N below 850 hPa (Figs. 10h-i) suggest more
480 intense shallow convection over marine low-level cloud regions in the Goddard than the
481 Dudhia control simulation, consistent with Fig. 8f.

482 Furthermore, it turns out that differences in the vertical profile of θ (Fig. 9) can only be
483 explained by those induced by SW radiations. The contribution of the latter to θ tendencies is
484 uniform and larger in almost the whole troposphere in the Goddard than the Dudhia control
485 simulation (Fig. 10f). The exception is around 300-200 hPa because of the large part of
486 downward SW radiations absorbed by O₃ above these levels by the Goddard SW scheme.
487 Differences in θ tendencies due to the remaining physical parameterizations are negative or
488 compensate each other.

489 Two main candidates contribute in explaining differences induced by the two SW
490 schemes: O₃ absorption in the Goddard scheme and the Dudhia scattering coefficient. Figure
491 11 investigates how these parameters modify the vertical stability of the atmosphere by
492 comparing zonal means of θ annual mean using simulations from Set #3 (Table 2). Fig. 11a
493 shows differences between the two control simulations. It is the same as Fig. 8b but for the
494 year 1989, and is shown as a baseline. Setting O₃ concentration to 0 sharply modifies θ near
495 the model top but does not modulate its vertical profile below (Fig. 11b). Associated
496 differences in latent heat fluxes and rainfall are weak in magnitude and quite noisy spatially
497 (not shown). This means that O₃ absorption does not explain the large differences between the
498 two control simulations and that modifying atmospheric temperatures above 300 hPa does not
499 significantly affect tropical climate in our simulations. Switching off the Dudhia scattering
500 does not warm the model top due to the absence of explicit O₃ absorption in the Dudhia
501 scheme, but does stabilize the atmosphere below so that differences with the Goddard control
502 simulation become insignificant (Fig. 11c). Similar results are obtained the way around, i.e.,
503 when comparing Dudhia simulations with and with no scattering (Fig. 11d). This indicates
504 that the strength of the Dudhia scattering coefficient drives the magnitude of differences

505 between the two SW schemes tested.

506 Figure 12 quantifies the sensitivity of the vertical profile in annual mean θ to the
507 strength of the Dudhia scattering coefficient. Results are similar over both sea and land points
508 (Figs. 12a-b). Differences remain large at 100 hPa whatever the scattering value due once
509 again to the absence of explicit O_3 absorption in the Dudhia scheme. On the other hand, they
510 sharply reduce below 100 hPa as the scattering value decreases, until turning positive with the
511 Dudhia scattering switched off. Decreasing the scattering coefficient acts thus in increasing
512 atmospheric stability over sea points where SSTs are prescribed, and shifting the whole
513 vertical profile of θ towards a warmer state over land points where surface temperatures
514 respond to SW radiations. This enhances thermal contrast between land and sea, hence
515 strengthens monsoon system and associated circulation.

516 Figure 13 quantifies to what extent the value of the Dudhia scattering coefficient
517 modulates the degree of agreement with the Goddard control simulation in the spatial
518 distribution and magnitude of SWnet_SFC, latent heat fluxes, and rainfall. Reducing the
519 Dudhia scattering coefficient results in both increased spatial agreement (Figs. 13a-c) and
520 reduced magnitude differences (Figs. 13d-f) with the Goddard control simulation. According
521 to the parameter and metric analyzed, the maximal consistency between the two SW schemes
522 is found when the Dudhia scattering coefficient ranges between \sim half its default value and 0.

523

524

525 **5. Discussion**

526

527 A large body of literature identifies CU parameterization as a significant, if not the
528 main, source of uncertainty for simulating tropical climate, while the impact of SW
529 parameterization is often neglected. Here, we disentangle the relative weight CU and SW
530 parameterizations have on tropical rainfall simulation by analyzing the 8 3/4° HR simulations
531 from Set #1 and from Set #4 (Table 2). We do not disentangle stratiform rainfall resolved by
532 MP and convective rainfall resolved by CU for brevity and because impact studies require
533 total rainfall to constrain hydrological and agronomic models. Results found for the total
534 rainfall do not necessarily prevail when disentangling stratiform and convective rainfall,
535 notably because the contribution of convective rainfall to total rainfall varies according to
536 both the CU scheme used and rainfall intensities considered (not shown).

537 Figure 14 focuses on the control CU and SW parameterizations have on the spatial
538 distribution and magnitude of annual mean rainfall. The box-and-whisker plots are the same

539 as in Figs. 5d-g but for the spread within the 2 CU and 2 SW ensembles. Regarding the spatial
540 distribution of rainfall over sea points (Fig. 14a, first four plots), the control of CU and SW
541 parameterizations is roughly the same and does not radically differ from that exerted by the
542 remaining settings tested in this study (Fig. 5d). This confirms that the spatial distribution of
543 rainfall over SST-prescribed regions depends on combined effects of different model settings.
544 This conclusion does not stand for land points (Fig. 14a, last four plots) where CU
545 parameterization drives the spatial distribution of rainfall, while SW parameterization has no
546 impact. The control of CU parameterization appears to be as important as that exerted by HR
547 (Fig. 5f), with the KF largely outperforming the BMJ scheme. On the other hand, SW
548 parameterization has the largest control on rainfall magnitude over both sea and land points
549 (Fig. 14b) and biases are very sensitive to the SW scheme used, especially over land points
550 where differences in rainfall biases reach 1 mm.day^{-1} between the two SW ensemble means,
551 against only $\sim 0.3 \text{ mm.day}^{-1}$ between the two CU ensemble means (Fig. 14b, last four plots).
552 This result unambiguously demonstrates that annual rainfall amounts are much more (i)
553 driven by SW than CU parameterization in these tropical simulations, and (ii) sensitive to the
554 SW than the CU schemes tested.

555 We finally analyze the control of CU and SW parameterizations on daily rainfall
556 distribution. We make use of a PDF-like approach consisting in weighting the probability of
557 occurrence of each rainfall bin according to their contribution to annual rainfall amounts so
558 that both the number of rainy events and their daily intensity are considered. For each
559 simulation, we extracted events in the space-time matrix (space: sea/land points within the
560 tropical-channel domain; time: the 365 days of the year 1989) for which daily rainfall amount
561 ranges between 0 and 1 mm.day^{-1} , and so on up to 100 mm.day^{-1} , every 1 mm.day^{-1} . We then
562 accumulate these amounts for each rainfall bin. The two CU and the two SW ensembles are
563 then constructed, and the same methodology is applied to the TRMM data for each year of the
564 1998 – 2007 period. Figures 15a-b present the results over sea and land points for the two CU
565 and the two SW ensemble means relative to the TRMM climatology. Figs. 15b-c show the
566 associated control of CU and SW parameterizations, computed as the coefficient of variation
567 within each ensemble (i.e., inter-member standard deviation divided by the ensemble mean)
568 for each rainfall bin. Results are summarized as follows:

- 569 • Model biases are physics dependent mainly for light rainy events over sea points (Fig.
570 15a: $\sim 0\text{-}5 \text{ mm.day}^{-1}$ range) with strong sensitivity to CU schemes, and for moderate rainy
571 events over land points (Fig. 15b: $\sim 20\text{-}40 \text{ mm.day}^{-1}$ range) with strong sensitivity to both CU
572 and SW schemes;

573 • The sign of differences between the two CU schemes varies according to rainfall bins
574 over both sea and land points, which is not the case between the two SW schemes. This
575 suggests that CU parameterization shapes the probability density function of rainfall, and that
576 SW parameterization controls rainfall intensity whatever the range considered;

577 • The control of CU and SW parameterizations is large over sea points, while rather
578 weak over land points, consistent with Fig. 15b. Over sea points (Fig. 15c), the contribution of
579 light rainy events is mostly controlled by CU parameterization, indicating that the latter is
580 critical for convection triggering under neutral atmospheric conditions. On the other hand, the
581 contribution of moderate rainy events ($\sim 20\text{-}50 \text{ mm}\cdot\text{day}^{-1}$) is further controlled by SW
582 parameterization, suggesting that large-scale atmospheric profiles are important for this range
583 of rainy events.

584

585

586 **6. Conclusion**

587

588 This study (i) highlights model deficiencies in representing the main components of the
589 energy budget and water cycle in the tropics that are insensitive to major model settings, (ii)
590 assesses the control SW parameterization has on tropical climate simulation relative to that of
591 the remaining model settings tested, and (iii) helps understanding the mechanisms by the
592 control of SW parameterization operates.

593 This is achieved by running 10-yr and 1-yr long tropical-channel simulations with
594 prescribed SSTs using the WRF model driven by the ERA-I reanalysis. Simulations include
595 sensitivity tests to the model physics (two schemes of SW, CU, and PBL parameterizations),
596 resolution (L45 and L60 VR, $3/4^\circ$ and $1/4^\circ$ HR), and to the way SW radiations (explicitly or
597 implicitly) interact with the atmosphere in the two SW schemes used. Analyses focus on the
598 spatial distribution and magnitude of SWnet_SFC, latent heat fluxes, and rainfall at the annual
599 timescale. The model skill is quantified relative to up-to-date observations (e.g., CERES-
600 EBAF, OAFlux, and TRMM).

601 Our tropical-channel simulations suffer from two main common deficiencies. First,
602 SWnet_SFC is systematically overestimated over regions where convection is deep (e.g., Fig.
603 2) due to the absence of feedback between convective clouds and SW radiations. Such
604 feedback has recently been incorporated into the WRF model V3.6 between the KF CU
605 scheme and the RRTMG (Rapid Radiative Transfer Model for global models) SW and LW
606 schemes (Alapaty et al. 2012). This feedback helps reducing downward SW radiations at the

607 surface over the U.S., which moderates the surface forcing for convection and results in
608 reduced rainfall biases. Second, latent heat fluxes are largely overestimated over warm pool
609 regions of the tropical ocean (Figs. 4a-b). One possible cause involves overestimated moisture
610 gradient between the surface and the subsurface due to too dry conditions simulated in the
611 low-troposphere. Other possible reasons involve overestimated radiative imbalance between
612 surface and atmosphere arising from the first deficiency, hence more need of latent heat
613 fluxes to compensate the imbalance excess (Wild and Liepert 2010), too strong surface –
614 atmosphere exchange coefficients and the absence of ocean – atmosphere coupling.

615 Among the model settings tested, SW parameterization has a paramount influence on
616 tropical climate, which is in line with, e.g., Pohl et al. (2011). SW parameterization clearly
617 drives the magnitude of SWnet_SFC (Fig. 1) and rainfall (Figs. 5, 14, and 15) and both the
618 spatial distribution and magnitude of latent heat fluxes over sea points (Fig. 3) in our model
619 configuration. This differs from findings by Di Luca et al. (2014) who state that latent heat
620 fluxes in the Mediterranean Sea is weakly sensitive to SW parameterization. The reason of
621 such disagreement involves differences in the experimental setup, with the use of strongly
622 constrained simulations (nudging applied above the PBL) by Di Luca et al. (2014), acting in
623 reducing the degree of freedom of their model. The impact of the remaining model settings is
624 nonetheless non negligible. The spatial distribution of rainfall mainly depends on CU
625 parameterization and HR over land. That of SWnet_SFC depends slightly more on PBL
626 parameterization and HR, which modify the location and/or intensity of low-marine clouds.
627 Note that including convective cloud – SW radiation feedbacks would probably increase the
628 control of SW and CU parameterizations on the spatial distribution of SWnet_SFC.

629 Despite their large influence on tropical climate, SW radiations remain challenging to
630 simulate and highly uncertain in climate models, as evidenced by large differences found
631 between Dudhia and Goddard SW simulations used in their default mode (Fig. 7). The model
632 skill depends on the metrics and parameters analyzed, so that none of the two SW schemes
633 systematically outperforms the other (Figs. 1-7). The two SW schemes profoundly modify the
634 vertical structure of the atmosphere according to the way they handle SW
635 absorption/reflection/scattering throughout the troposphere and whether surface responds to
636 SW forcing or not. The Goddard absorbs much more downward SW than the Dudhia scheme
637 (Figs. 8-12). The reason is the scattering coefficient used in the Dudhia SW scheme for
638 emulating aerosol and Rayleigh scattering, and stratospheric ozone and aerosol absorption
639 (Fig. 11). The surplus of SW absorption further stabilizes the troposphere over sea where
640 surface temperatures are prescribed (i.e., sea points), while results in a shift towards a warmer

641 state over land where surface is coupled to atmosphere (i.e., land points). The consequences
642 are less (more) latent heat fluxes and rainfall simulated by the Goddard than the Dudhia SW
643 scheme over sea (land) points. Decreasing the Dudhia scattering coefficient allows sharp
644 increase in SW absorption, so that differences between the two SW schemes are cancelled out
645 or reversed when switching off the scattering coefficient in the Dudhia SW scheme (Figs. 12-
646 13).

647 This study demonstrates the usefulness of tropical-channel simulations to investigate
648 tropical climate dependency to the model physics and resolutions. It also highlights the need
649 for improving SW parameterization, which is not only the main driver of tropical climate but
650 also one of the most uncertain components of the model physics. Additional work is needed to
651 quantify to what extent the inclusion of convective cloud – SW radiation feedbacks improves
652 the model skill in simulating tropical climate, to understand the impact of the remaining
653 model settings tested in this study, and to test the robustness of our results in an air-sea
654 coupled framework with the Nemo – Oasis – WRF modeling system (Samson et al. 2014).

655

656

657 **Acknowledgments**

658

659 This work was funded by the European Commission's 7th Framework Programme, under
660 Grant Agreement number 282672, EMBRACE project, and by the project PULSATION
661 ANR-11-MONU-0010 of the French National Research Agency (ANR). WRF was provided
662 by the University Corporation for Atmospheric Research
663 (http://www2.mmm.ucar.edu/wrf/users/download/get_source.htm). Simulations are performed
664 on the Curie supercomputer, owned by GENCI and operated into the TGCC by CEA. We
665 acknowledge PRACE for awarding us access to the Curie supercomputer through its 3rd, 5th
666 and 9th calls. We also thank the two anonymous reviewers for their helpful comments.

667

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822 **Table Captions**

823

824 **Table 1:** List of the main acronyms used.

825

826 **Table 2:** Summary of the 4 sets of simulations used with grey shadings showing the
827 settings tested.

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829

830 **Figure Captions**

831

832 **Figure 1:** (a) Annual mean climatology in the net SW radiation budget at the surface
833 (SWnet_SFC; W.m⁻²) under full-sky conditions for the CERES-EBAF data interpolated onto
834 the grid of 3/4° simulations. (b-c) Same as (a) but for the Dudhia and Goddard SW ensemble
835 means from Set #1. (d) Box-and-whisker plots for the Bravais-Pearson linear correlation (r) in
836 the annual mean climatology of tropical-channel SWnet_SFC between the 16 simulations
837 from Set #1 and the CERES-EBAF data. The two first box-and-whisker plots contain the 8
838 members of the Dudhia and Goddard SW ensembles, respectively. The 3 next pairs of box-
839 and-whisker plots are the same, but for the two PBL, VR, and HR ensembles, respectively
840 (see Table 1 for acronyms). Note that 1/4° HR simulations are interpolated onto the grid of
841 3/4° HR simulations. The boxes have lines at the lower quartile, median and upper quartile
842 values. The whiskers are lines extending from each end of the boxes and show the extent of
843 the range of the data within 1.5 by interquartile range from the upper and lower quartiles.
844 Stars are r values for ensemble means and plus signs are outliers. (e) Same as (d) but for the
845 model root mean square errors (RMSE).

846

847 **Figure 2:** (a-b) Biases in the annual mean climatology of SWnet_SFC (W.m⁻²) under
848 full-sky conditions for the Dudhia and Goddard SW ensemble means from Set #1,
849 respectively, with respect to the CERES-EBAF data. (c-d) Same as (a-b) but under cloudy-
850 sky conditions for the two 1-yr long SW ensembles from Set #2.

851

852 **Figure 3:** (a) Annual mean climatology in latent heat fluxes (W.m⁻²) for the OAFlux data
853 interpolated onto the grid of 3/4° HR simulations. (b-c) Same as Figs. 1d-e but for latent heat
854 fluxes over sea points within the tropical-channel domain.

855

856 **Figure 4:** (a-b) Biases in the annual mean climatology of latent heat fluxes (W.m⁻²) for
857 the Dudhia and Goddard SW ensemble means from Set #1, respectively. (c-d and e-f) Same
858 as (a-b) but for 10m wind speed (m.s⁻¹) and 2m specific humidity (g.kg⁻¹) biases against the
859 ERA-I and OAFlux data, respectively.

860

861 **Figure 5:** (a) Annual mean climatology in rainfall (mm.day⁻¹) for the TRMM data
862 interpolated onto the grid of 3/4° HR simulations. (b-c) Same as Figs. 1d-e but for rainfall. (d-

863 e and f-g) Same as (b-c) but for sea and land points within the tropical-channel domain,
864 respectively.

865

866 **Figure 6:** (a-b) Biases in the annual mean climatology of rainfall ($\text{mm}\cdot\text{day}^{-1}$) for the
867 Dudhia and Goddard SW ensemble means from Set #1, respectively. (c-d) Same as (a-b) but
868 for 1000 to 700 hPa vertically-averaged moisture fluxes (vectors) and moisture flux
869 convergence (shadings) biases against the ERA-I data.

870

871 **Figure 7:** Differences in the annual mean climatology of (a) SWnet_SFC, (b) rainfall, (c)
872 latent heat fluxes, and (d) 1000 to 700 hPa vertically-averaged moisture fluxes (vectors) and
873 moisture flux convergence (shadings) between the Goddard and Dudhia SW ensemble means
874 from Set #1.

875

876 **Figure 8:** (a) Vertical-meridional cross-section in the annual mean climatology of
877 potential temperature (K) averaged over sea points for the Goddard SW ensemble mean from
878 Set #1. (b) Differences between the Goddard and Dudhia SW ensemble means (contours
879 every 0.2 K). (c-d and e-f) Same as (a-b) but for vertical velocity ($\text{m}\cdot\text{s}^{-1}$) and cloud fraction
880 from the microphysics (ratio) with contours every 0.0005 $\text{m}\cdot\text{s}^{-1}$ and 0.01, respectively. In (c)
881 and (d) positive velocity is upward.

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883 **Figure 9:** Differences in the vertical profile of the annual mean climatology of potential
884 temperature averaged over sea (purple) and land (green) points between the Goddard and
885 Dudhia SW ensembles from Set #1. Solid lines show the differences between the 8 members
886 of the Goddard and Dudhia SW ensembles. Bold lines show the differences between the two
887 ensemble means.

888

889 **Figure 10:** (a-e) Vertical-meridional cross-section of potential temperature tendencies due
890 to the parameterization of SW, LW, CU, MP, and PBL for the Goddard control simulation
891 from Set #3, respectively (see Table 1 for acronyms). Tendencies are accumulated at the daily
892 timescale then averaged over the year 1989. (f-j) Same as (a-e) but for the differences
893 between the Goddard and Dudhia control simulations from Set #3.

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895 **Figure 11:** Vertical-meridional cross-section in the differences of potential temperature
896 (K) between (a) the two control simulations from Set #3, (b) the Goddard control simulation

897 and that with no O₃ absorption, (c) the Goddard control simulation and the Dudhia simulation
898 with no scattering, and (d) between the Dudhia simulation with no scattering and the Dudhia
899 control simulation.

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901 **Figure 12:** Differences in the vertical profile of annual mean potential temperature
902 averaged over (a) sea and (b) land points between the Goddard control simulation and the 11
903 Dudhia simulations with the scattering coefficient varying from 2×10^{-5} to 0 every 0.2×10^{-5} .
904 The black line is zero difference.

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906 **Figure 13:** Spatial correlation in the annual mean (a) SWnet_SFC, (b) latent heat fluxes,
907 and (c) rainfall between the Goddard control simulation and 10 Dudhia simulations with the
908 scattering coefficient varying from 2×10^{-5} to 0 every 0.2×10^{-5} . (d-f) Same as (a-c) but area-
909 averaged differences. Black circles correspond to all grid points within the tropical-channel
910 domain. Green and purple dots denote land and sea points within the tropical-channel domain,
911 respectively.

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913 **Figure 14:** Same as Figs. 5d-g but for the two CU and SW ensembles.

914

915 **Figure 15:** Biases of the two CU and SW ensemble means in rainfall amounts
916 accumulated over (a) sea and (b) land points within the tropical-channel domain for the year
917 1989 according to daily rainfall intensity. Ranges of rainfall intensity vary from 0 to 100
918 mm.day⁻¹, every 1 mm.day⁻¹. Biases are computed against the TRMM climatology computed
919 for the 1998 – 2007 period. (c-d) Same as (a-b) but for the coefficient of variation of each
920 ensemble (%) computed as the ratio between the inter-member standard deviation and the
921 ensemble mean.

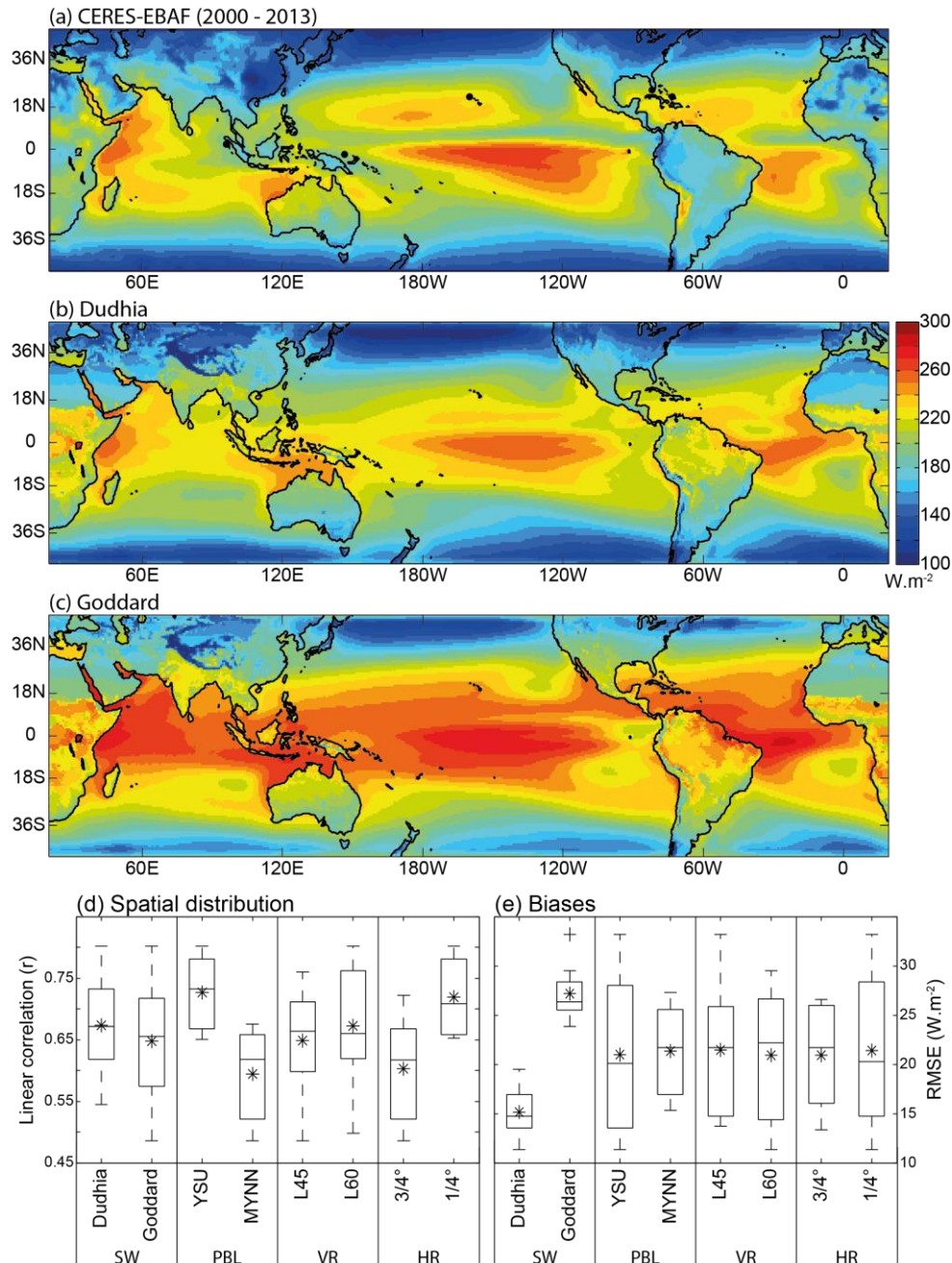
922	Models and data	
923	CERES-EBAF	Cloud and Earth's Radiant Energy System Energy Balanced and Filled (edition 2.8)
924	CMIP5	Climate Model Intercomparison Project Phase 5
925	ERA-I	ERA-Interim reanalysis
926	GCM	Global Climate Model
927	OAFflux	Objectively Analysed air-sea Heat Fluxes (version 3)
928	RCM	Regional Climate Model
929	TRMM	NASA 3B42-V7 Tropical Rainfall Measuring Mission
930	WRF	Weather Research and Forecasting
931	Model settings	
932	CU	convection
933	HR	horizontal resolution
934	LSM	Land Surface Model
935	LW	longwave
936	MP	microphysics
937	PBL	planetary boundary layer
938	SW	shortwave
939	VR	vertical resolution
940		
941	L45	45 layers in the vertical
942	L60	60 layers in the vertical
943	Other	
944	ITCZ	Inter-Tropical Convergence Zone
945	RMSE	root mean square errors
946	SST	sea surface temperature
947	SWnet_SFC	net SW radiation budget at the surface
948	θ	potential temperature

954
955 **Table 1:** List of the main acronyms used.

	Duration	SW		PBL		VR		HR		CU	
		Dudhia	Goddard	YSU	MYNN	L45	L60	3/4°	1/4°	BMJ	KF
Set #1	10 years	all combinations tested with the BMJ CU scheme: 16 simulations									
Set #2	1 year	additional diagnostics: full-/clear-sky; temperature tendencies due to the physics									
Set #3		varying scattering coefficient	with/no O ₃								
Set #4											

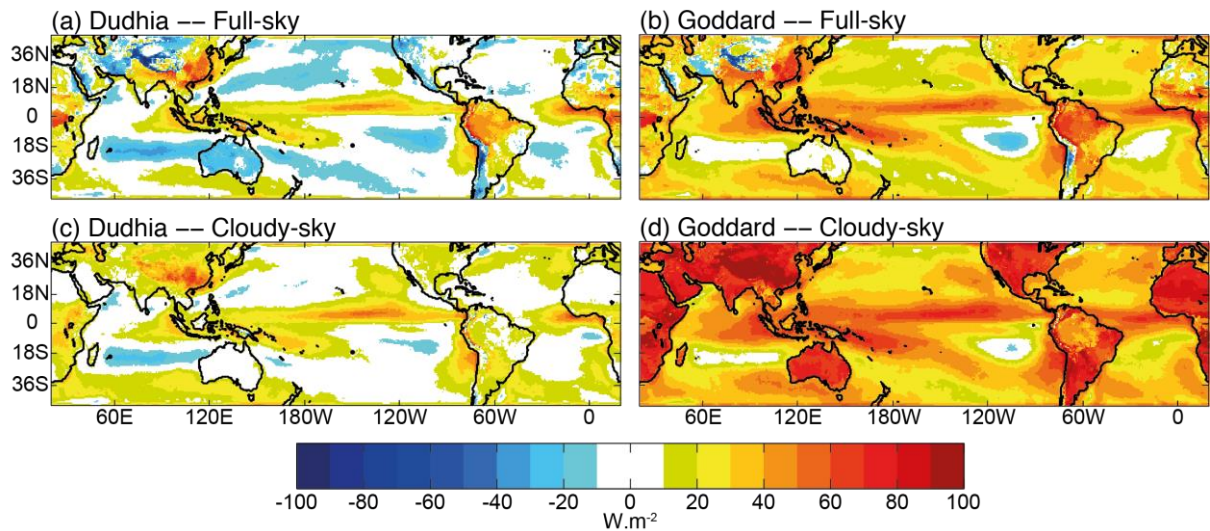
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Table 2: Summary of the 4 sets of simulations used with grey shadings showing the settings tested.



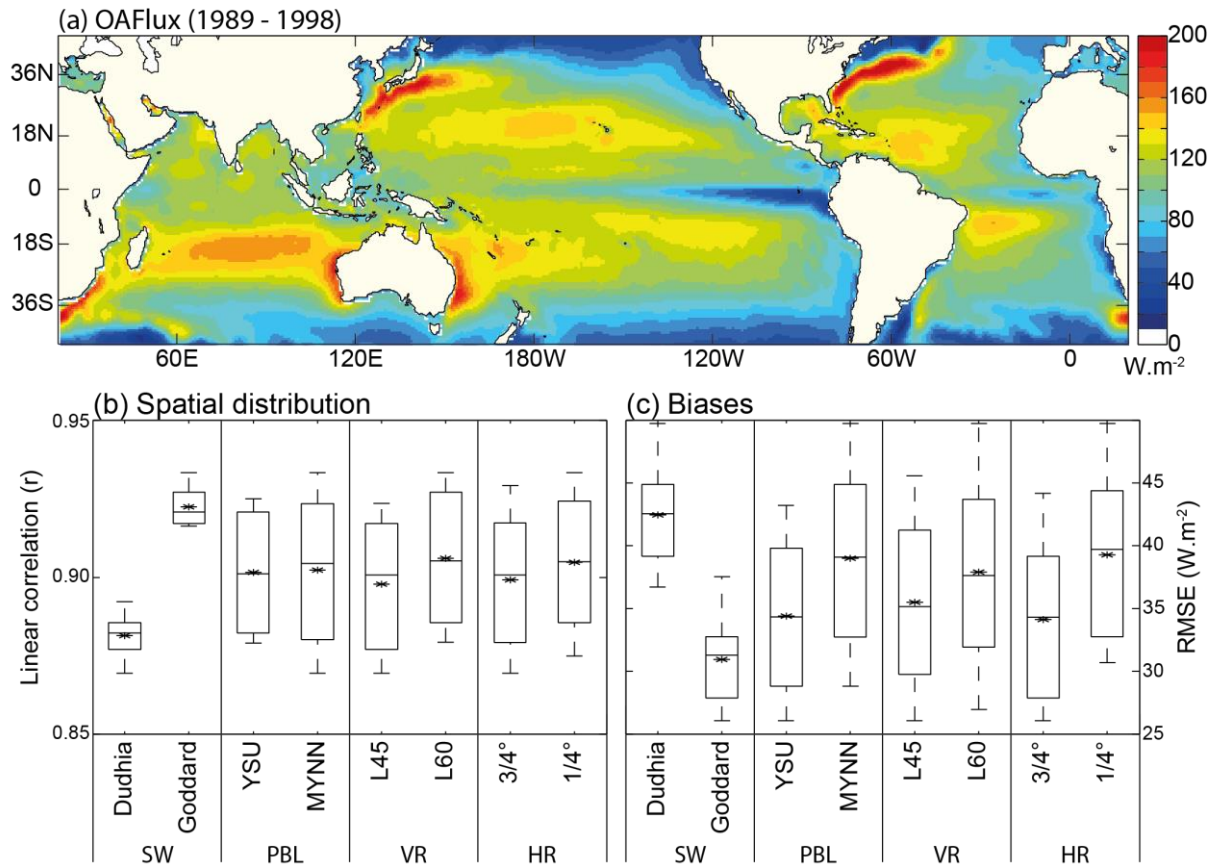
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 962 (SWnet_SFC; $W.m^{-2}$) under full-sky conditions for the CERES-EBAF data interpolated onto
 963 the grid of $3/4^\circ$ simulations. (b-c) Same as (a) but for the Dudhia and Goddard SW ensemble
 964 means from Set #1. (d) Box-and-whisker plots for the Bravais-Pearson linear correlation (r) in
 965 the annual mean climatology of tropical-channel SWnet_SFC between the 16 simulations
 966 from Set #1 and the CERES-EBAF data. The two first box-and-whisker plots contain the 8
 967 members of the Dudhia and Goddard SW ensembles, respectively. The 3 next pairs of box-
 968 and-whisker plots are the same, but for the two PBL, VR, and HR ensembles, respectively
 969 (see Table 1 for acronyms). Note that $1/4^\circ$ HR simulations are interpolated onto the grid of
 970 $3/4^\circ$ HR simulations. The boxes have lines at the lower quartile, median and upper quartile
 971 values. The whiskers are lines extending from each end of the boxes and show the extent of
 972 the range of the data within 1.5 by interquartile range from the upper and lower quartiles.
 973 Stars are r values for ensemble means and plus signs are outliers. (e) Same as (d) but for the
 974 model root mean square errors (RMSE).



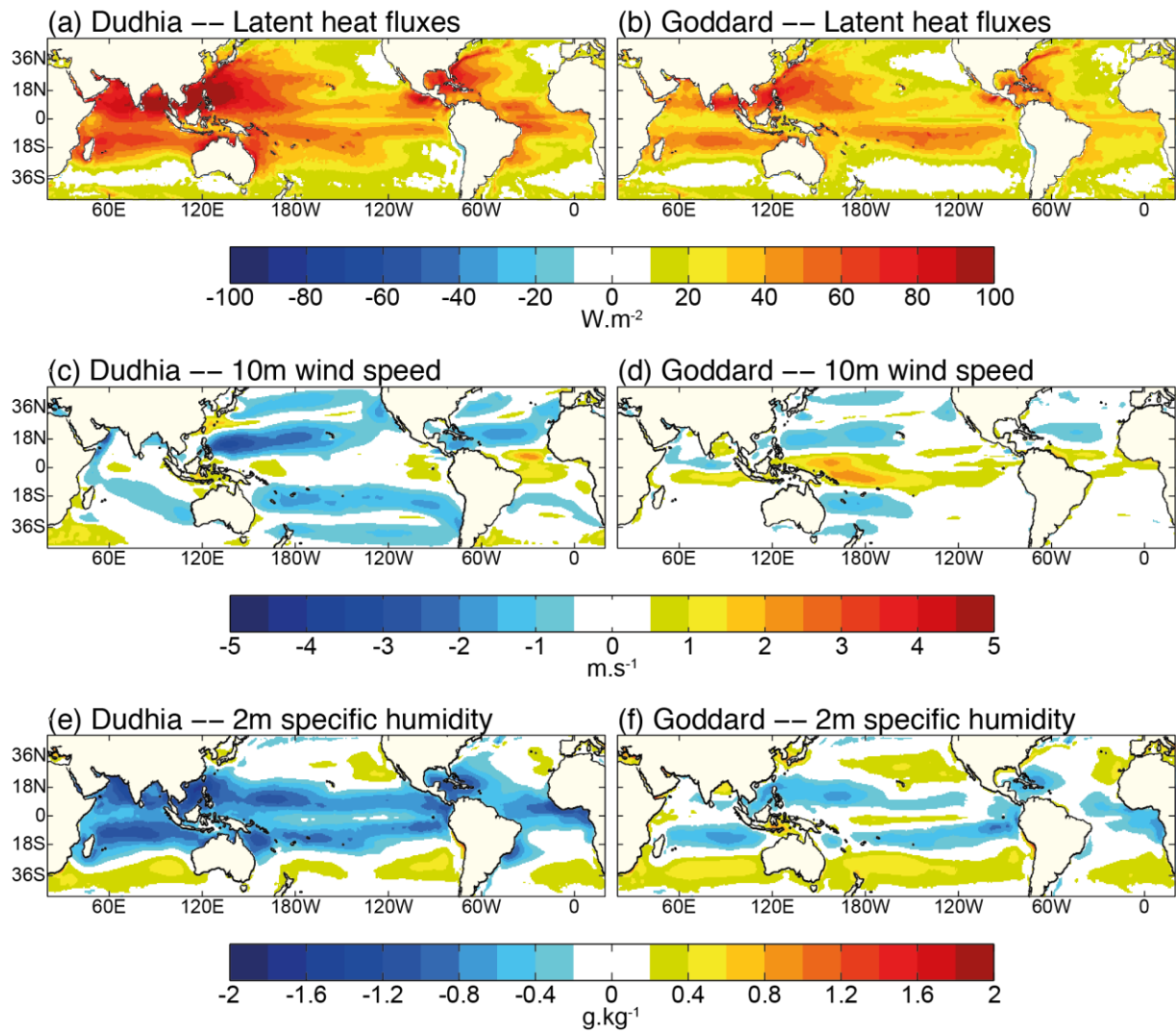
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Figure 2: (a-b) Biases in the annual mean climatology of SWnet_SFC (W.m^{-2}) under full-sky conditions for the Dudhia and Goddard SW ensemble means from Set #1, respectively, with respect to the CERES-EBAF data. (c-d) Same as (a-b) but under cloudy-sky conditions for the two 1-yr long SW ensembles from Set #2.



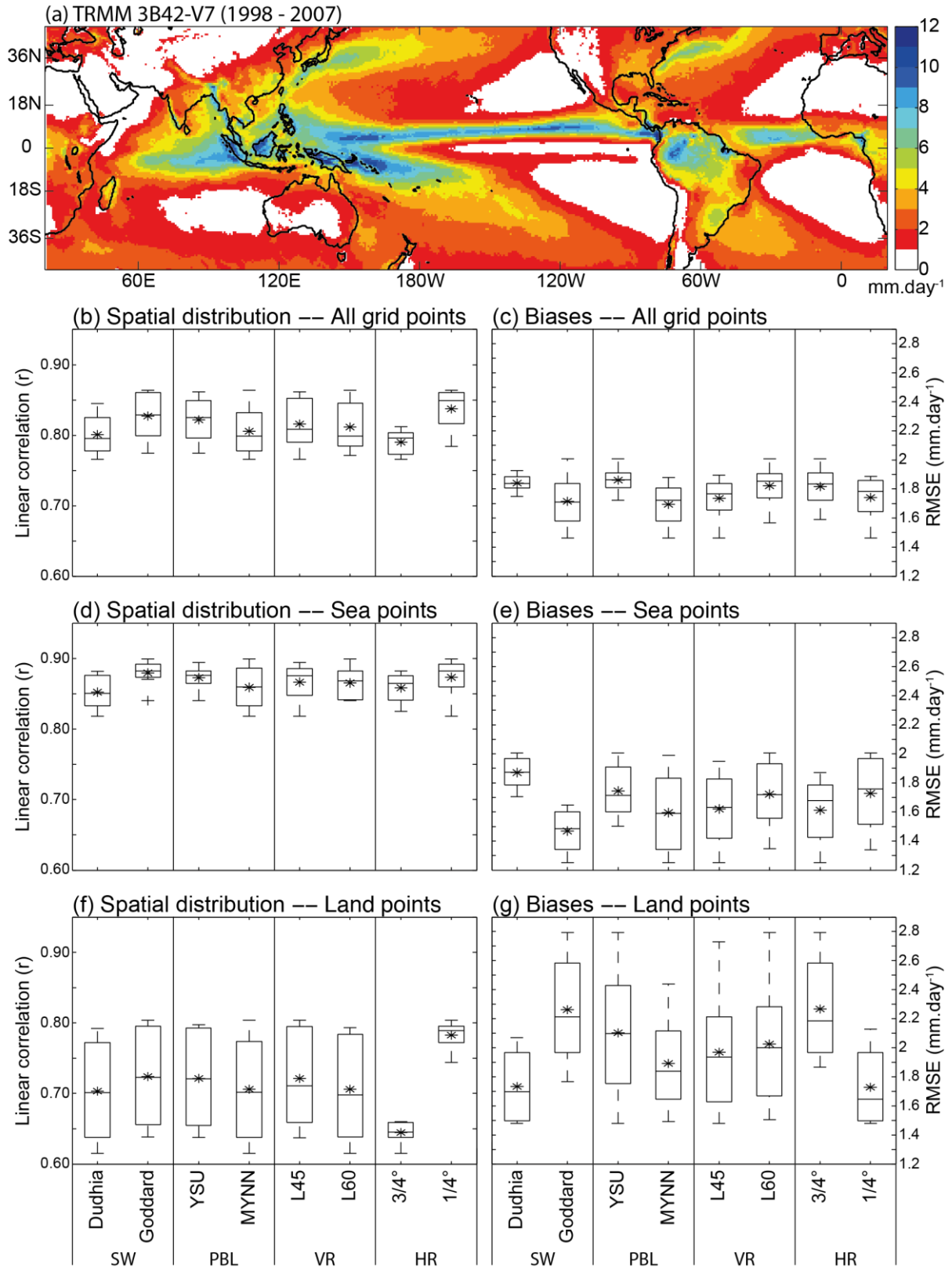
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Figure 3: (a) Annual mean climatology in latent heat fluxes ($W.m^{-2}$) for the OAFlex data interpolated onto the grid of $3/4^\circ$ HR simulations. (b-c) Same as Figs. 1d-e but for latent heat fluxes over sea points within the tropical-channel domain.



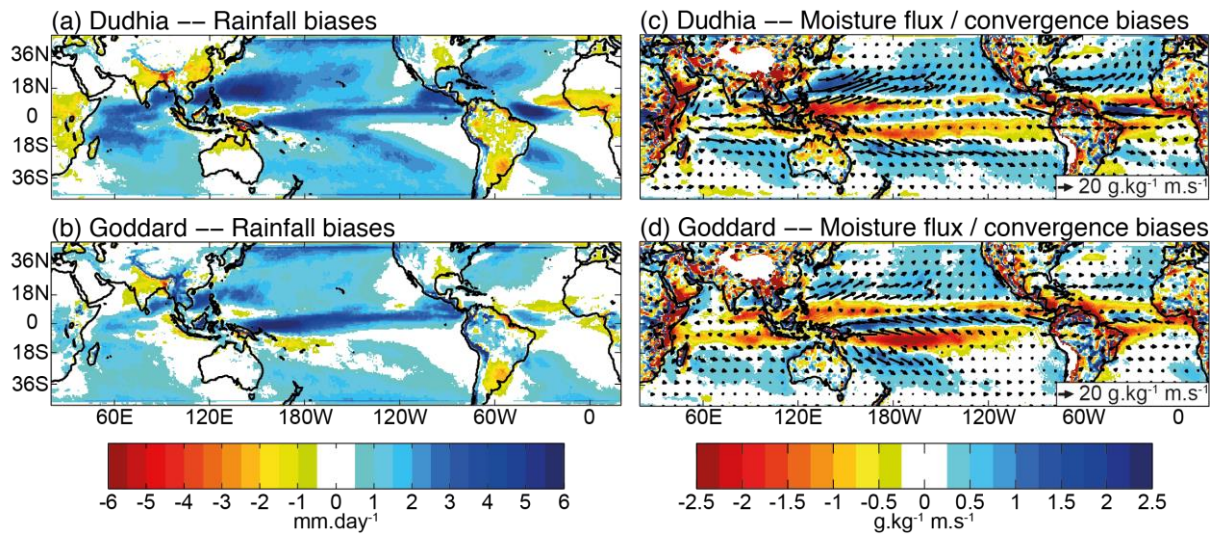
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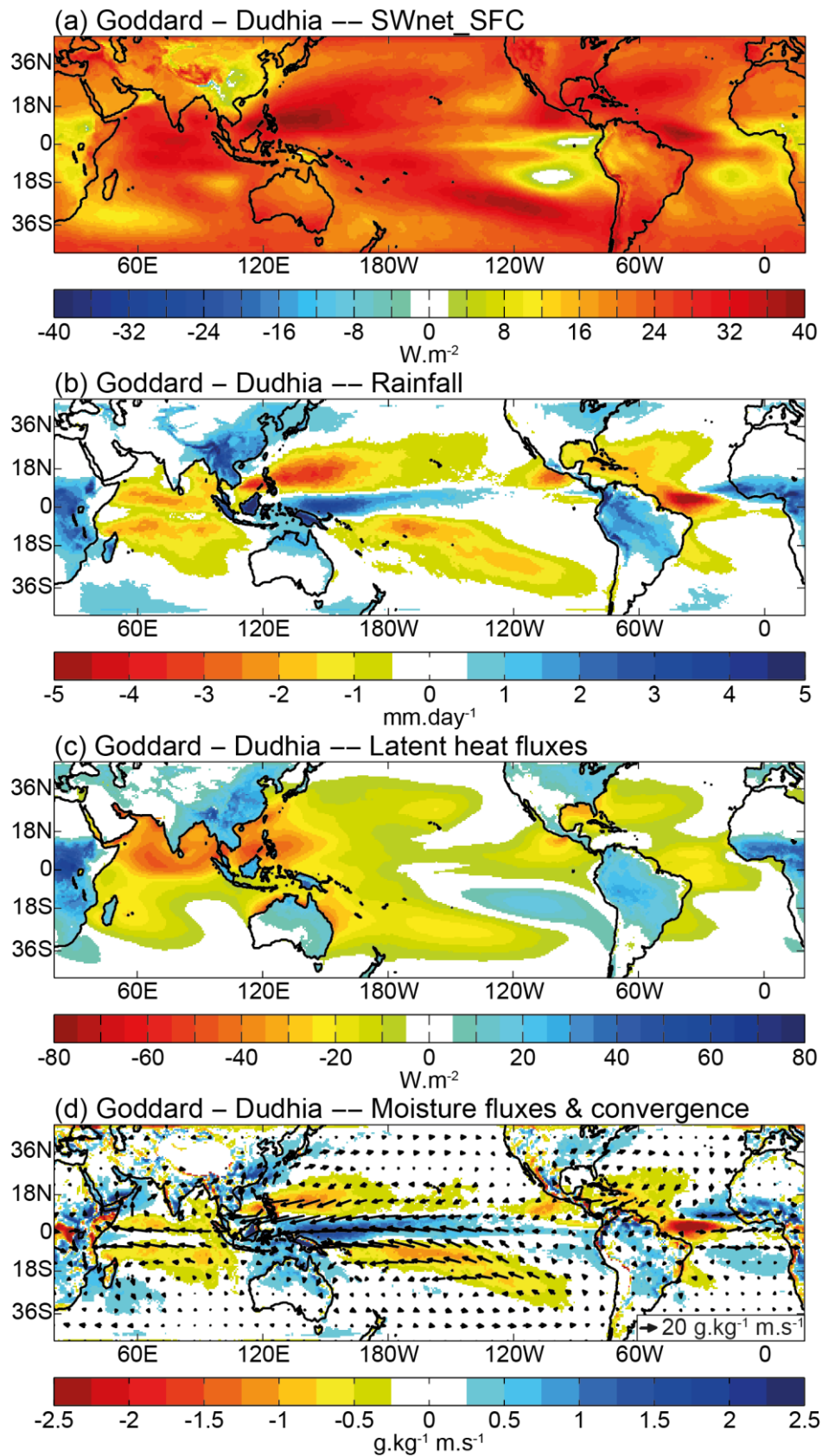
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Figure 5: (a) Annual mean climatology in rainfall (mm.day⁻¹) for the TRMM data interpolated onto the grid of 3/4° HR simulations. (b-c) Same as Figs. 1d-e but for rainfall. (d-e and f-g) Same as (b-c) but for sea and land points within the tropical-channel domain, respectively.



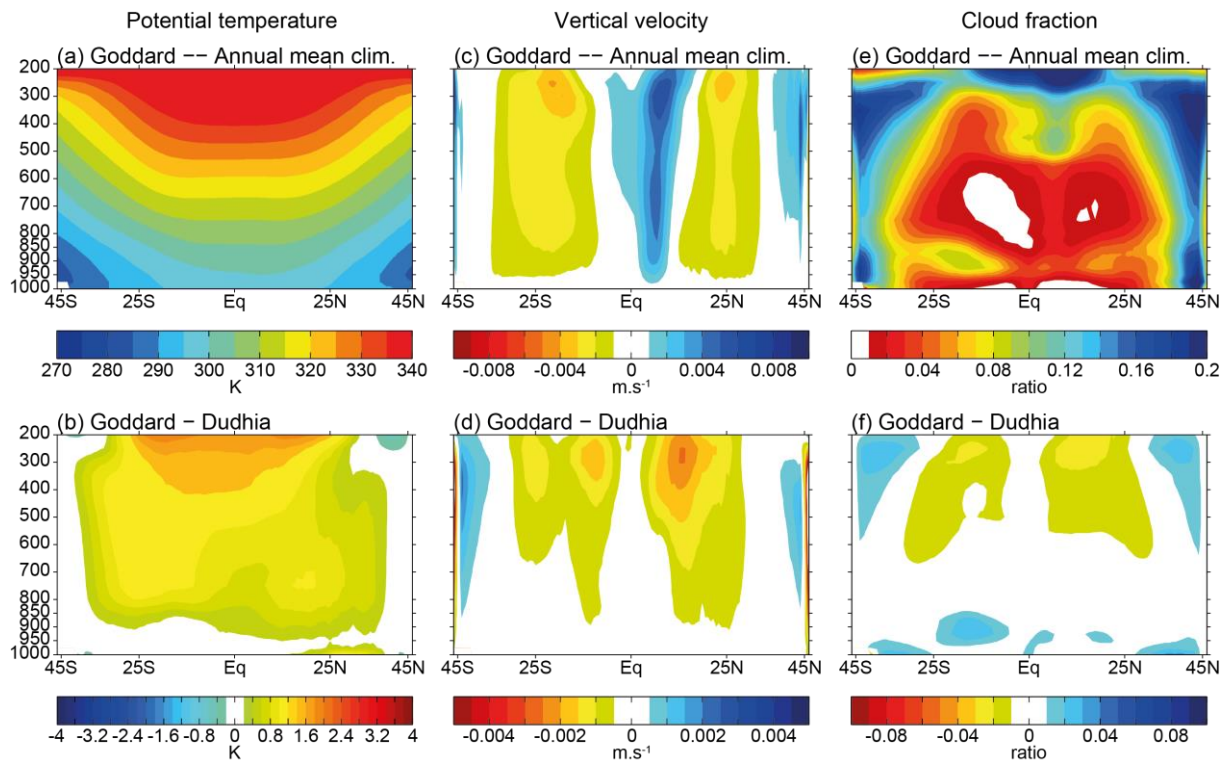
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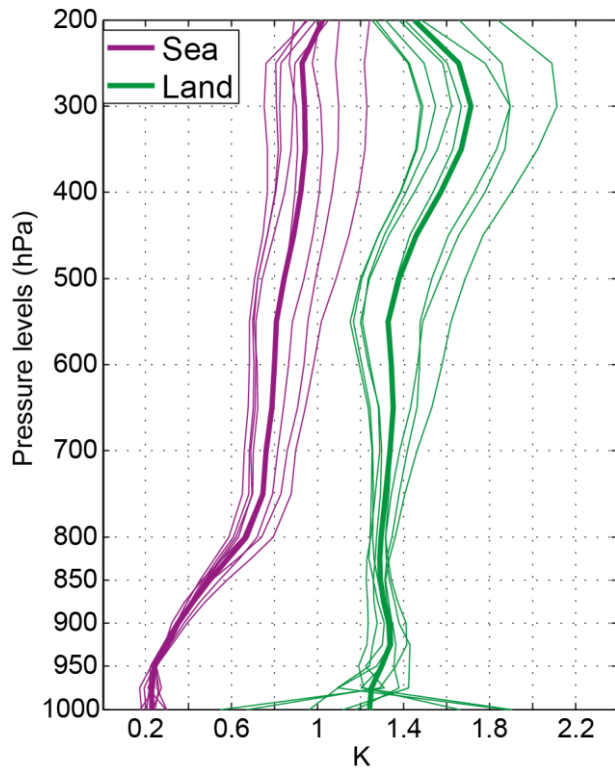
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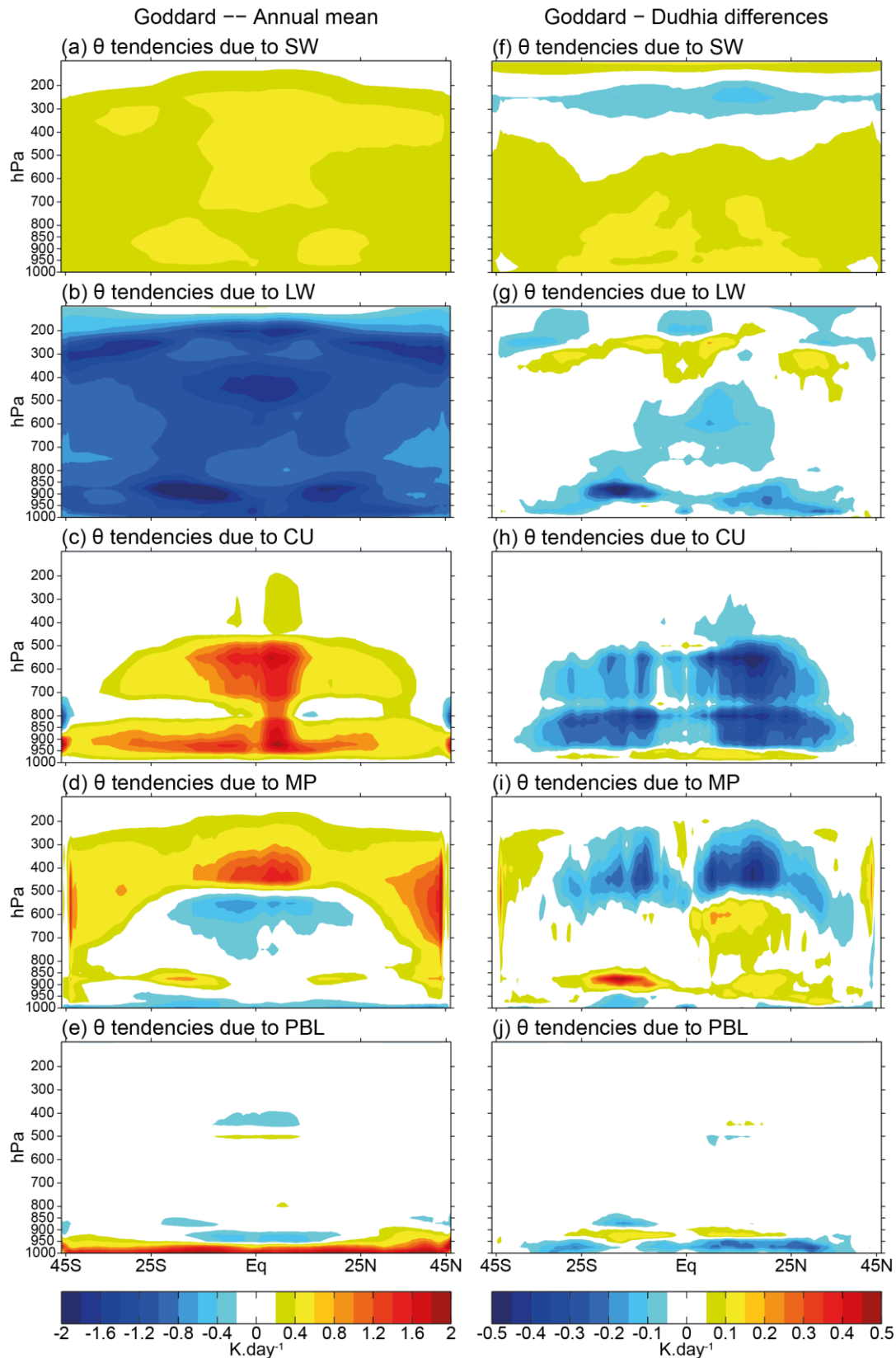
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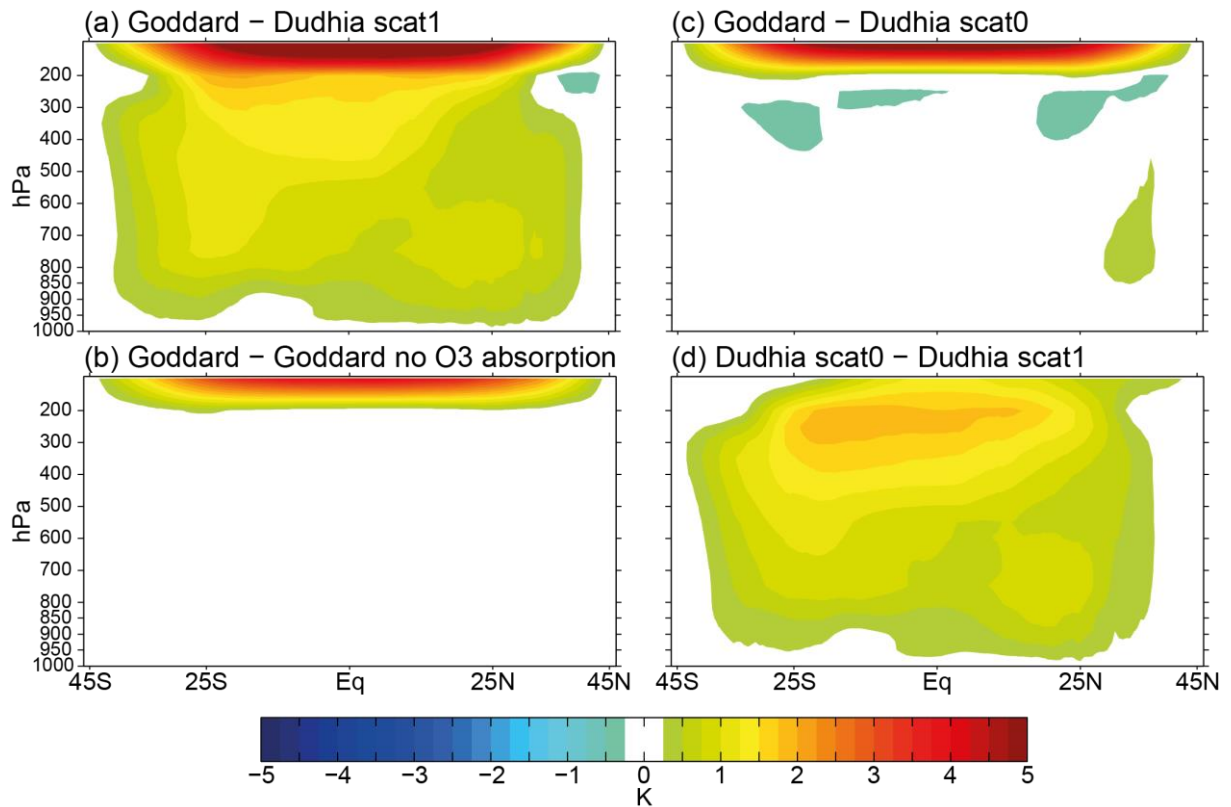
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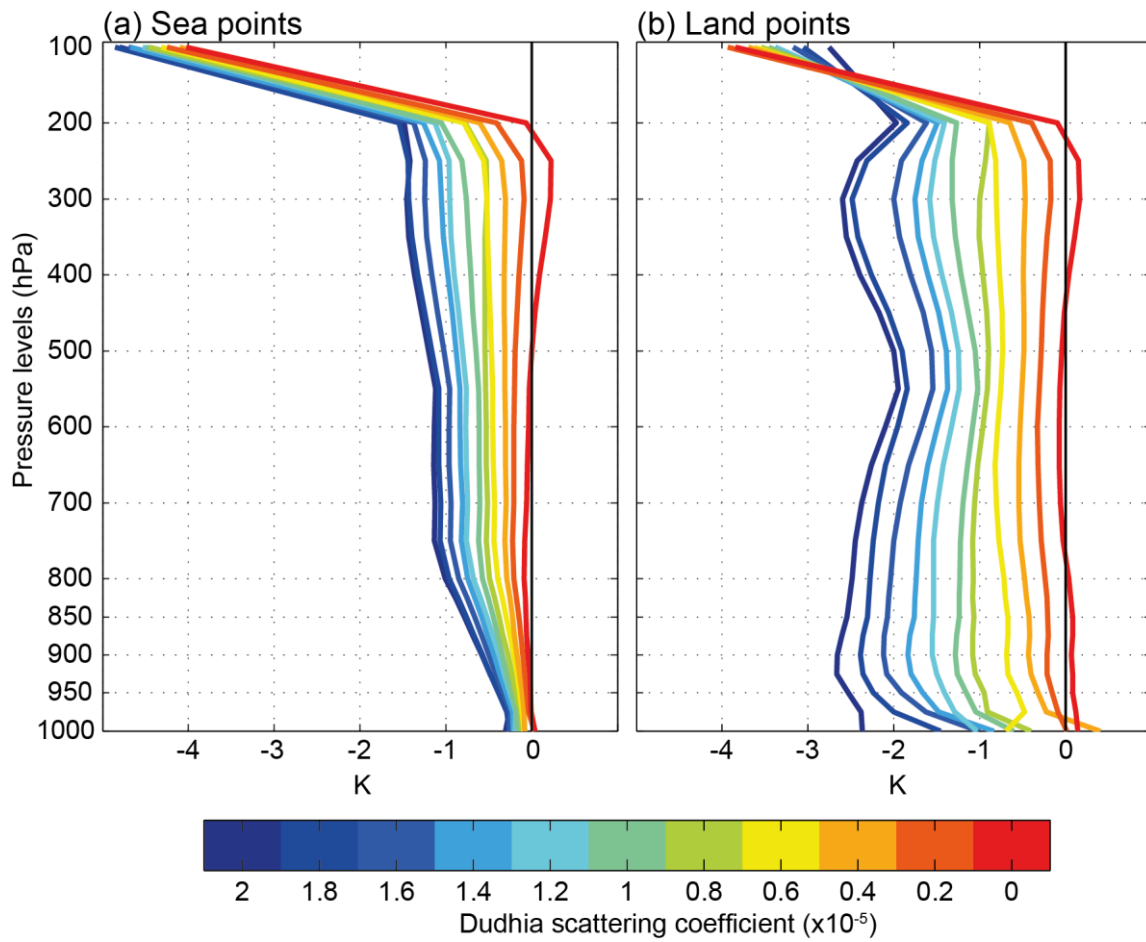
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Figure 10: (a-e) Vertical-meridional cross-section of potential temperature tendencies due to the parameterization of SW, LW, CU, MP, and PBL for the Goddard control simulation from Set #3, respectively (see Table 1 for acronyms). Tendencies are accumulated at the daily timescale then averaged over the year 1989. (f-j) Same as (a-e) but for the differences between the Goddard and Dudhia control simulations from Set #3.



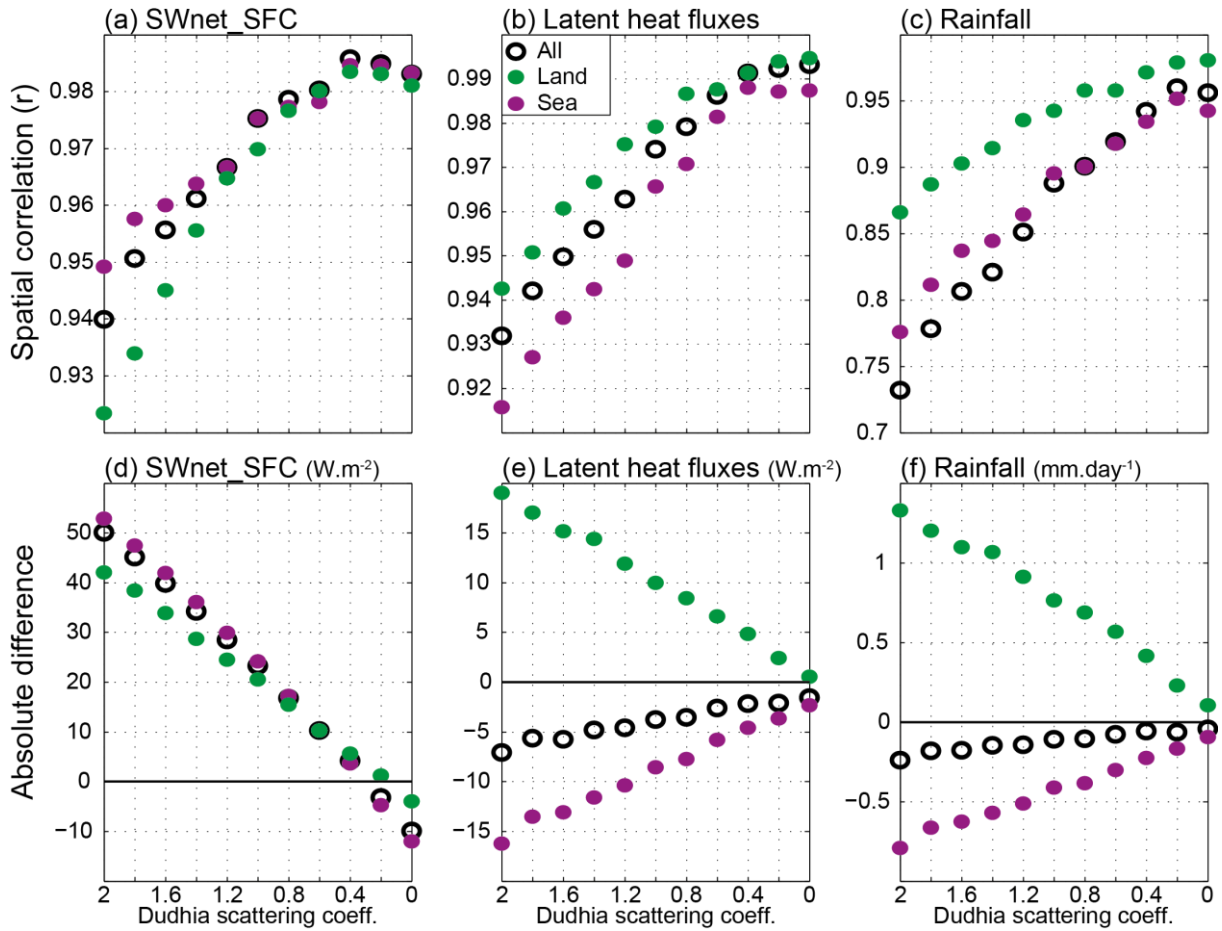
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Figure 11: Vertical-meridional cross-section in the differences of potential temperature (K) between (a) the two control simulations from Set #3, (b) the Goddard control simulation and that with no O₃ absorption, (c) the Goddard control simulation and the Dudhia simulation with no scattering, and (d) between the Dudhia simulation with no scattering and the Dudhia control simulation.



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Figure 12: Differences in the vertical profile of annual mean potential temperature averaged over (a) sea and (b) land points between the Goddard control simulation and the 10 Dudhia simulations with the scattering coefficient varying from 2×10^{-5} to 0 every 0.2×10^{-5} . The black line is zero difference.



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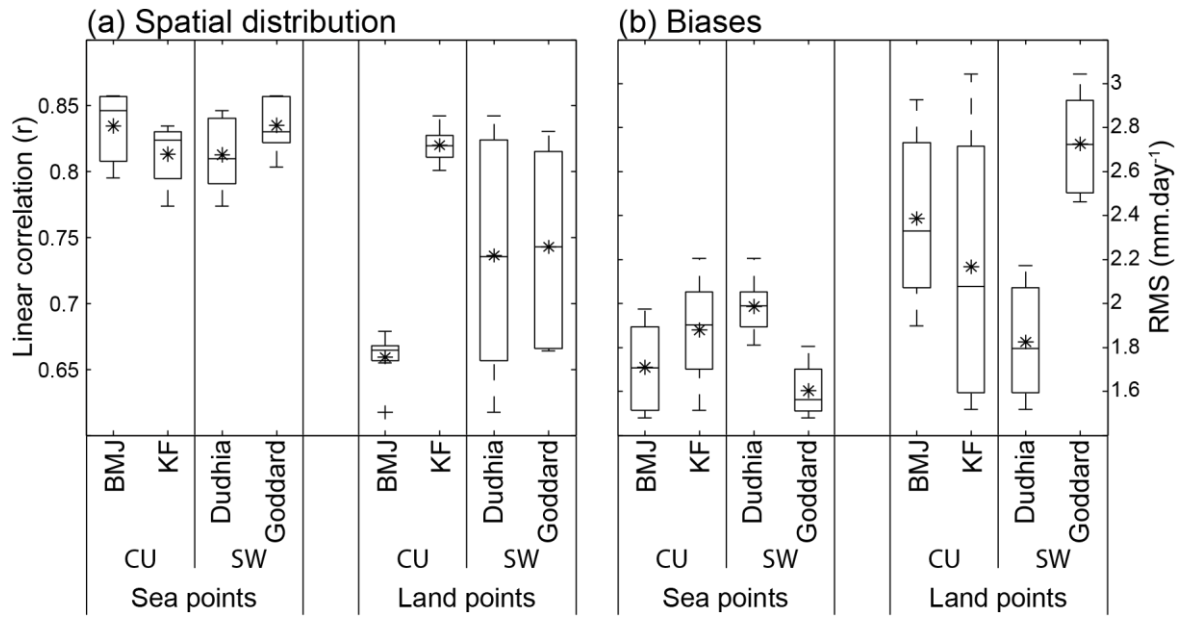
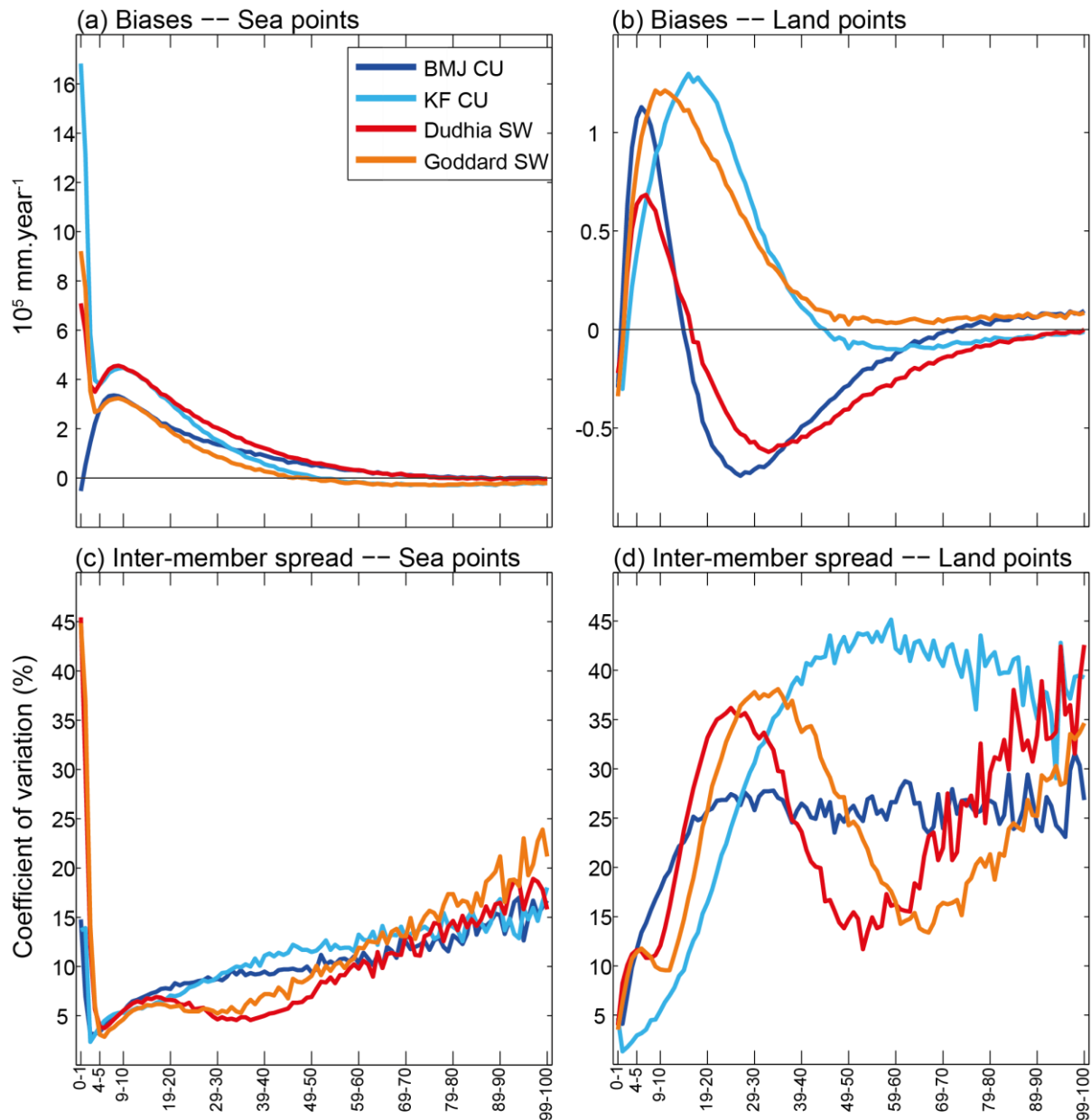


Figure 14: Same as Figs. 5d-g but for the two CU and SW ensembles.

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Figure 15: Biases of the two CU and SW ensemble means in rainfall amounts accumulated over (a) sea and (b) land points within the tropical-channel domain for the year 1989 according to daily rainfall intensity. Ranges of rainfall intensity vary from 0 to 100 mm.day⁻¹, every 1 mm.day⁻¹. Biases are computed against the TRMM climatology computed for the 1998 – 2007 period. (c-d) Same as (a-b) but for the coefficient of variation of each ensemble (%) computed as the ratio between the inter-member standard deviation and the ensemble mean.