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**A modeling analysis of rainfall and water cycle by the cloud-resolving
WRF model over western North Pacific**

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22 Abstract

23 This study simulates regional precipitation, especially extreme precipitation events,
24 and the regional hydrologic budgets over the western North Pacific region during the
25 period from May to June 2008 by the high-resolution (4-km grid spacing) Weather
26 Research and Forecast (WRF v3.2.1) model with explicit cloud microphysics. The
27 model initial and boundary conditions are derived from NCEP/DOE R2 reanalysis
28 data.

29 Adopting the retrieved rainfall from Tropical Rainfall Measuring Mission (TRMM)
30 3B42 as a reference for comparison, the WRF simulations reproduce the spatial
31 distributions of time mean precipitation amount and rainy days. But the simulated
32 frequency distributions of rainy days and rainfall amount show overestimated light
33 precipitation, underestimated moderate to heavy precipitation, and well simulated
34 extreme precipitation. The vapor budget analysis shows that the heavy precipitation is
35 contributed mostly by the stronger moisture convergence. However, in less convective
36 periods, the precipitation is more influenced by the surface evaporation. The vapor
37 budget is sensitive to the cloud microphysics scheme that affects the location and
38 strength of atmospheric latent heating and then the large-scale circulation.

39 **1. Introduction**

40 Precipitation is an essential parameter describing the monsoon climate. The spatial
41 distribution of precipitation indicates the location of atmospheric heat source, and the
42 precipitation evolution reflects the variability of monsoon circulation system.
43 Meanwhile, precipitation is also a key component of the earth's hydrological cycle.
44 Studying precipitation characteristics is essentially important for understanding
45 monsoon circulation and its relationship with other components of the hydrological
46 cycle. However, an accurate simulation of summer precipitation, particularly for
47 tropical regions, remains a major challenge due to the frequent local-scale convective
48 activity [Jenkins, 1997; Kunkel et al., 2002]. Modeling and predicting the tropical
49 atmosphere phenomena such as summer monsoons activity, tropical convection, and
50 cloud microphysical variable are still deficient for the lack of fundamental knowledge
51 over the tropic ocean.

52 The East Asian (EA) monsoon and western North Pacific (WNP) monsoon affect
53 not only the regional climate but also the vicinity of the region and even the global
54 climate through hydrological and energy exchange processes [Lau and Weng, 2002].
55 In the past two decades, many researches on the WNP summer monsoon by using the
56 reanalysis data and satellite precipitation dataset had been conducted [Murakami and
57 Matsumoto, 1994; Wang et al., 2001; Wang and LinHo, 2002; Conroy and Overpeck,
58 2011]. The climate over WNP region depends not only on the atmospheric, but also
59 on the oceanic conditions of tropical and subtropical regions. So, the moisture
60 transport and hydrological cycle over the EA-WNP region are more complex than

61 those over other regions. For example, the sources of water vapor variations over the
62 EA-WNP region commonly come from three areas: the northern Indian Ocean, the
63 South China Sea (SCS, including the cross-equatorial transport), and the western
64 North Pacific [Zhou and Yu, 2005; Ding and Sikka, 2006]. Furthermore, the spatial
65 heterogeneity of rainfall in this region may respond nonlinearly to changes in forcing
66 factors [Zhou et al., 2009]. For lack of conventional observations, to present,
67 relatively few studies have been dedicated to the regional model performance over the
68 WNP region. Our study will focus on the climatology during the onset of SCS-WNP
69 summer monsoon in the period from May to June 2008.

70 It is known that the existing global general circulation models (GCMs) horizontal
71 grid intervals are too coarse for applications at regional scale regimes [Leung et al.,
72 2003; Giorgi, 2006]. To mitigate this problem, a dynamical downscaling strategy to
73 obtain regional weather phenomena influenced by the local topography or small-scale
74 atmospheric features has been conducted in many previous studies [Giorgi, 1990;
75 Christensen et al., 1998; Liang et al., 2004; Kanamitsu and Kanamaru, 2007], in
76 which GCM or reanalysis data are used to provide lateral boundary condition, sea
77 surface temperature, and initial land-surface conditions for more spatially-detailed
78 climatologically simulations over a region of interest. The dynamical downscaling
79 method is supposed to retain the large-scale circulation, and is intended to add
80 information on the smaller scales that the coarse-resolution global model could not
81 generate [Castro et al., 2005]. Note that the regional models can add value, but for
82 certain variables and locations. Winterfeldt et al. [2010] argued that the dynamical

83 downscaling does not add value to the global reanalysis wind speed in open ocean
84 areas because of the relatively homogeneous topography over the ocean. In addition,
85 the effects of spatial resolution on regional climate simulations have been discussed
86 extensively. Leung and Qian [2003] analyzed the results of 5 yr regional simulations
87 for the Pacific Northwest and California, and demonstrated that the 13-km nest
88 produces more realistic seasonal mean precipitation as well as more frequent heavy
89 precipitation compared to the 40-km nest, which are in closer agreement with the
90 observations. Kobayashi and Sugi [2004] showed that the climatology of synoptic
91 scale phenomena is well represented and tropical cyclones occurred more frequently
92 with higher intensities when increasing global model resolution, improving the
93 simulation of Asian monsoon. Improving the precipitation simulation with higher
94 spatial resolution was generally reported in many climate studies due to the detailed
95 representation of terrain effects and spatial heterogeneity. But now, most of the
96 regional climate simulations still use a relatively coarse grid resolution (about 10-40
97 km).

98 In addition, Randall et al. [2007] pointed out that the cumulus parameterization
99 used in GCMs is another major cause of ambiguity for climate simulation. The details
100 of cloud microphysics scheme are expected to be introduced into regional climate
101 studies instead of the cumulus parameterization. A global cloud resolving simulation
102 with a mesh size of a few kilometers was conducted using a nonhydrostatic
103 icosahedral atmospheric model (NICAM) [Miura et al., 2007]. Satoh et al. [2008]
104 showed that the relative occurrence of rainfall rate from NICAM is in agreement with

105 that of the TRMM PR dataset for strong rains over the oceans. Tao et al. [2003]
106 simulated the mesoscale convective systems over South China Sea with a regional
107 climate model and a cloud-resolving model, and indicated that proper simulation of
108 precipitation processes probably needs cloud-scale models. However, until recently,
109 few models have been run with just explicit microphysics (without using cumulus
110 parameterizations) and with fine enough grid spacing (1-4 km) to investigate the
111 regional climate mechanisms.

112 The long-term goal of this study is to refine our understanding of clouds and
113 precipitation over tropical Pacific warm pool and western North Pacific interacting
114 with climate oscillations at seasonal or longer time scales. So the basic properties of
115 simulated precipitation as well as regional water cycle in the high-resolution
116 dynamical downscaling framework should be explored first. With this aim, several
117 questions are addressed: (1) How well does the WRF high-resolution downscaling
118 simulated precipitation agree with the observations over the WNP region? (2) Is the
119 microphysics crucial for adequate performance of climatological precipitation over
120 the ocean? (3) How well does the WRF model represent the regional hydrologic
121 budgets?

122 The primary focus of this paper is to investigate the capability of cloud-resolving
123 WRF model in simulating the characteristics of regional precipitation, especially
124 extreme precipitation events as well as the regional hydrologic budgets over the
125 western North Pacific. The paper is organized as following: Section 2 describes the
126 model, data and experimental design. Section 3 examines the thermodynamic

127 variables. The comparisons of observed and simulated daily mean precipitation,
128 percentage of rainy days, precipitation frequency distribution and extreme
129 precipitation are presented in section 4. The hydrologic budgets are discussed in
130 section 5, and a summary is given in section 6.

131 **2. Model, data and experimental design**

132 **2.1 Model description**

133 The model employed here is the Weather Research and Forecast (WRF) model
134 version 3.2.1 [Skamarock et al., 2008]. The WRF model is a mesoscale numerical
135 weather system designed for short-term weather forecast as well as long-term climate
136 simulation. It is a non-hydrostatic, terrain-following mesoscale model, and is being
137 developed and studied by a broad community of researchers in the recent years.

138 The Chinese Academy of Meteorological Sciences (CAMS) two-moment
139 microphysics is adopted in this study as an alternative microphysical scheme. It was
140 developed by Hu and He [1988] and had been tested and employed in many previous
141 studies [Hu and He, 1989; Lou et al., 2003; Li et al., 2008; Gao et al., 2011a, 2011b].

142 A total of 11 microphysical variables including the mixing ratio of vapor, the mixing
143 ratios and number concentrations of cloud droplet, rain, cloud ice, snow, and graupel
144 are predicted in CAMS microphysics. In the past years, the scheme has received many
145 significant improvements, such as accurate calculation of supersaturation, detailed
146 treatment of autoconversion and droplet nucleation parameterization. Gao et al.
147 [2011b] evaluated and improved the CAMS raindrop microphysical parameterization
148 against the Southwest Monsoon Experiment (SoWMEX) /Terrain-influenced

149 Monsoon Rainfall Experiment (TiMREX) observations in June 2008.

150 **2.2. Validation dataset**

151 The Tropical Rainfall Measuring Mission (TRMM) 3B42 rainfall estimation
152 version 6, which is a high spatial (0.25° by 0.25°) and high temporal (3 h)
153 satellite-derived precipitation dataset available in the latitude band 50^0S - 50^0N from 1
154 January 1998 to present. These data are created by blending passive microwave data
155 collected by low earth orbit satellites [such as TRMM Microwave Imager (TMI),
156 Special Sensor Microwave Imager (SSM/I), Advanced Microwave Scanning
157 Radiometer (AMSR), Advanced Microwave Sounding Unit (AMSU)], and the
158 infrared (IR) data collected by the international constellation of geosynchronous earth
159 orbit (GEO) based on calibration by the precipitation estimate of the TMI-PR
160 combined algorithm. The physically based combined microwave estimates are used
161 where available, and the remaining grid boxes are filled with microwave calibrated IR
162 estimates [Huffman et al., 2007].

163 **2.3 Experimental design**

164 The model domain is designed to consist of three one-way nested domains as shown
165 in Fig. 1. The numbers of grid points and corresponding horizontal grid resolutions for
166 domains 1, 2, 3 are $290 \times 210 \times 35$ at 36-km, $541 \times 421 \times 35$ at 12-km and 883×691
167 $\times 35$ points at 4-km, respectively. The lateral boundary condition is specified at the
168 lateral boundary grid points and the neighboring 4-grid relaxation zone. To capture the
169 large-scale processes important for Pacific Northwest climate, the outermost domain

170 encompasses nearly the entire East and Central Asia continent and much of the
171 western Pacific Ocean. The use of such a large outer domain keeps the outer
172 boundaries far from the innermost domain to ensure that weather systems approaching
173 the Pacific Northwest are free from lateral boundary influences. The second nested
174 domain covers the East Asia continent and the western North Pacific, capturing the
175 tropical convections and East Asian monsoon circulations that influence the Pacific
176 Northwest. The innermost domain covers the South China Sea and portions of the
177 western North Pacific.

178 For non-hydrostatic cloud resolving models, the choice of horizontal and vertical
179 grid resolutions is always an important issue. Different resolutions in such models can
180 have a major impact on the resolved convective processes [Weisman et al. 1997;
181 Tompkins and Emanuel 2000]. Weisman et al. [1997] suggested that a minimum grid
182 length of 4 km is necessary to reasonably simulate the internal structures and
183 mesoscale circulations of a midlatitude squall line. Tompkins and Emanuel [2000]
184 suggested that a high vertical resolution (less than 33 hPa) is needed to develop a high
185 degree of vertical structure in water vapor profiles and stratiform precipitation
186 processes. The effect of resolution on simulated cloud systems has also been
187 performed by evaluations of simulated clouds against observed cloud quantities [e.g.
188 Johnson et al. 2002; Satoh et al. 2010, 2012 and references therein]. Satoh et al. [2010,
189 2012] compared the simulated cloud properties by a global cloud resolving model
190 with a mesh sizes of 3.5, 7 and 14 km with satellite data. They found that the general
191 characteristics of the cloud distribution are similar, but the cloud thickness and the

192 size of the mesoscale convective system depend quantitatively on resolution. Based
193 on the above considerations and on the limitation of the computer resources, we
194 choose the mesh size of 4 km in the current study.

195 The initial and lateral boundary conditions are interpolated from the NCEP/DOE
196 reanalysis 2 data (hereafter R2) [Kanamitsu et al., 2002]. The lateral boundary
197 conditions are updated every 6 hours. The sea surface temperature (SST) from R2
198 data is also updated every 6 hours. The physics schemes used are Noah land surface
199 model [Chen and Dudhia, 2001], Yonsei University (YSU) planetary boundary-layer
200 scheme [Hong et al., 2006], Grell-Devenyi cumulus parameterization [Grell and
201 Devenyi, 2002], rapid radiative transfer model long-wave radiation [Mlawer et al.,
202 1997] and Dudhia short-wave radiation [Dudhia, 1989]. No cumulus parameterization
203 is used in domain 3. In order to assess the impact of microphysics on the precipitation
204 process in 4-km model resolution, two microphysics schemes are conducted: Goddard
205 3ICE [Tao and Simpson, 1993] and CAMS. Goddard 3ICE is a one-moment scheme,
206 it predicts only the mixing ratios for five hydrometeor species. Goddard scheme is
207 mainly based on Lin et al. [1983] with additional processes from Rutledge and Hobbs
208 [1984]. Several modifications have been made in the past years. e.g., new saturation
209 techniques [Tao et al., 2003] are added; all microphysical processes that do not
210 involve melting, evaporation or sublimation are calculated based on one
211 thermodynamic state; the sum of all sink processes associated with one species will
212 not exceed its mass. Whereas, CAMS is a two-moment scheme, it predicts both the
213 mixing ratios and number concentrations for five hydrometeor species (including

214 droplet number).

215 The simulation period is from 0000 UTC 1 May to 2400 UTC 30 June 2008. The
216 model is re-initialized every 2 days. Each re-initialization runs for 12 hours
217 proceeding the initial time of each 2-day simulation by nudging the horizontal winds
218 above 850 hPa at each grid toward the reanalysis values. The re-initialization is a
219 simple spin-up run to produce a set of initial fields every two days in the two-month
220 integration period to mitigate the climate drift in regional climate simulations
221 [Dickinson et al., 1989; Qian et al., 2003]. Grid nudging is applied in the two outer
222 model domains (D1 and D2) but not in the innermost domain (D3), which allows the
223 mesoscale model to freely develop atmospheric structure at finer spatial scale. The
224 model outputs at every 6 hours are used for the evaluation.

225 **3. Evaluation of model thermodynamic variables**

226 To evaluate the state variables, we compare the model simulated temperature and
227 humidity with R2 data. Figure 2 shows the difference of mean dry static energy
228 ($DSE=c_pT+gz$, where C_p is the specific heat at constant pressure, T absolute
229 temperature, g the gravitational acceleration and z the height above surface) and latent
230 heat energy (L_vq , where L_v is the latent heat of vaporization, q the water vapor mixing
231 ratio) averaged over domain 3 during May to June 2008 between WRF simulations
232 and R2 reanalysis. The value of DSE shown in Fig. 2 is determined mainly by the air
233 temperature. The model simulated temperature by the two cloud schemes differ from
234 the R2 data within 1°C, and the CAMS scheme simulated temperature is slightly
235 warmer than that in Goddard scheme. Compared with the R2 data, the two simulations

236 show a common warm bias in the upper troposphere above 200 hPa, and a common
237 cold bias in the low troposphere below 850 hPa. Associated with the model cold bias in
238 the lower troposphere, model results also show a common moist bias. But the two cloud
239 schemes produce opposite moisture bias above 850 hPa. More latent heat release,
240 which results in heating the atmosphere, is likely responsible for the warmer and more
241 humid air above the boundary layer in CAMS scheme than those in Goddard scheme
242 through the thermodynamic feedback processes. But the common moist and cold
243 biases in the two WRF simulations are indicative of deficiencies in the model boundary
244 layer process.

245 The diurnal cycles of model temperature and humidity are further examined by
246 forming a diurnal composite of vertically integrated saturation water vapor mixing ratio
247 (q_s) and water vapor mixing ratio (q) averaged over domain 3 from 30 consecutive
248 two-day integrations during May to June 2008. The composite q_s and q are shown in
249 Fig. 3a and 3b, respectively. Since q_s is function of temperature, the diurnal q_s from R2
250 shows a maximum value near 06 UTC (local time 3 pm) and a cooling trend toward a
251 minimum value near 24 UTC (local time 9 am) with an amplitude of about 4 kg m^{-2} .
252 The two WRF simulations show a similar diurnal change characterized by a warm
253 phase near 06 to 12 UTC and a cold phase near 18 to 24 UTC with a smoother phase
254 change and a weaker amplitude than that of R2 data. The difference between the
255 simulated and assimilated q_s is clearly resulted from the cloud radiative interactions in
256 the cloud-resolving physics. The higher q_s from CAMS scheme than that from Goddard
257 scheme (by about 2.4 kg m^{-2}) is consistent with the difference in simulated DSE profiles

258 shown in Fig. 2a. The composite curves of q for the model and R2 data show very
259 weaker diurnal cycles with no consistent phase changes. This indicates that the water
260 vapor field in the domain of interest is dominated by synoptic scale disturbances. The
261 simulated q by CAMS is somewhat larger than that by Goddard, but the simulated
262 precipitation by CAMS is significantly larger than that by Goddard which is correlated
263 with the moisture convergence. This will be discussed in detail in section 5.

264 **4. Evaluation of model precipitation**

265 Precipitation is an important quantity for climate studies, and reducing the
266 precipitation bias is one of the major goals for regional climate simulations. The
267 TRMM 3B42 daily precipitation data are used as a reference in this study. The R2
268 reanalysis data and WRF simulations are spatially re-gridded onto 0.25 grid points,
269 the same as the TRMM dataset, for comparison purpose. Note that no interpolation is
270 used when calculating the precipitation frequency.

271 **4.1 Mean precipitation pattern**

272 Figure 4 shows the spatial distribution of time mean precipitation during May to
273 June 2008 from TRMM observations, R2 reanalysis, and WRF simulations. The
274 major monsoon rainbands are located over the Philippine Sea, South China Sea, and
275 the southeast China coast. The location of rainfall center over the ocean is near the
276 9.5°N , 131°E , and the maximum value is about 21 mm day^{-1} (Figure 4a). The WRF
277 simulations reproduce the characteristics of daily mean precipitation well with the
278 TRMM observations. The patterns of spatial distribution from WRF model clearly
279 show an improvement compared with R2 reanalysis, which has a wet bias over the

280 ocean, and has a strong dry bias over the southeast China coast. The Goddard scheme
281 reduces the wet bias of R2 reanalysis over the ocean; on the contrary, the CAMS
282 scheme introduces a wet bias relative to R2 reanalysis. Although the CAMS scheme
283 produces the maximum daily mean precipitation with a value about 21 mm day^{-1} over
284 the ocean, similar to the TRMM observation, it overestimates the range of heavy
285 precipitation. The spatial distributions of daily mean precipitation in Fig. 4 show that
286 the two microphysics schemes produce similar precipitation patterns, but different
287 precipitation amount.

288 To quantitatively evaluate the performances of WRF model in simulation of
289 precipitation, the time mean precipitation averaged over domain 3, the pattern root
290 mean square error (RMSE) and pattern correlation coefficients with respect to the
291 TRMM observations are listed in Table 1. Also included in the Table is the time mean
292 precipitation from the assimilation product R2. Results show that the simulated spatial
293 and temporal mean precipitation in Goddard scheme is slightly less than observation,
294 while that in CAMS scheme is somewhat larger than observation, indicating that
295 climatological precipitation in the northwest Pacific warm monsoon season is sensitive
296 to cloud microphysics scheme. This is consistent with the finding that the skill in
297 simulating tropical precipitation systems is generally poorer than that in mid-latitude
298 systems [Wang et al., 2003; Lee et al., 2004] due to weak baroclinic instability and
299 complicated physical processes in East Asia. Table 1 further shows that the time mean
300 patterns of precipitation simulated by the high-resolution WRF with the two
301 microphysics schemes have smaller pattern RMSE and higher pattern correlation with

302 the TRMM precipitation than that produced by R2. This indicates that the high
303 resolution WRF with an explicit cloud microphysics can reasonably resolve mesoscale
304 variability, and is capable of simulating accumulated precipitation distribution in
305 properly designed regional climate downscaling simulation.

306 **4.2 Temporal evolution of the precipitation**

307 The model performances in reproducing the northward migration of tropical and
308 subtropical fronts and associated rain bands are examined. Figure 5 shows the
309 time-latitude cross-section of daily precipitation along the longitudinal band between
310 110° and 145°E. Two major phases of northward movement of convection zone from
311 near the equator to about 25°N are observed (middle of May and end of June). The
312 average speed of northward propagation is about 1.0° latitude per day. The northward
313 movement reflects the seasonal migration of the EA-WNP monsoon rain bands. The
314 WRF model and R2 reanalysis generally reproduce the two northward marches of rain
315 bands. But, they all fail to simulate the weak northward rain band from 10° to 25°N in
316 the period from end May to early June. In addition, the temporal correlation
317 coefficients between TRMM observed and WRF simulated daily precipitation are
318 similar to that between TRMM observed and R2 reanalysis (area averaged ~ 0.34),
319 indicating that the current WRF downscaling simulation is not improving the
320 temporary variability significantly. Since many atmospheric variability fields which
321 lead to precipitation are constrained by observations twice a day in the reanalysis data,
322 so no obvious improvements are made in the timing of precipitation.

323 **4.3 Precipitation frequency**

324 We next analyze frequency distributions of rainy days and precipitation. The
325 percentages of all days with precipitation exceeding 0.1 mm day^{-1} (the definition of
326 rainy day in this study) and 50 mm day^{-1} during May to June 2008 are calculated.

327 The percentage of rainy days is largely affected by the re-gridded data [Osborn and
328 Hulme, 1997; Ensor and Robeson, 2008], which will potentially generate systematic
329 biases in the comparison. For example, the averaged precipitation frequency of rainy
330 days will increase about 15 % when using the re-gridded data instead of the original
331 data in our study. So, we use the results from all the original model outputs and do not
332 interpolate them to the resolution of TRMM observations when calculating the
333 precipitation frequency. This approach helps to directly derive information from the
334 model itself, especially for models with a relatively high resolution [Sun et al., 2006].

335 The percentage of rainy days in TRMM dataset is higher over the southernmost and
336 northernmost of domain 3. The R2 reanalysis overestimates the frequency of rainy
337 days over the ocean compared to the TRMM dataset. As we expect, the patterns of
338 rainy day frequency are improved in WRF simulations than that in R2 reanalysis
339 (Figure 6). The WRF simulations evidently reduce the percentage of rainy days in the
340 southern part of domain and increase that in the northern part of domain, conforms to
341 the TRMM observations. Note that the CAMS two-moment scheme produces a little
342 more rainy days than that from Goddard one-moment scheme (there exist areas where
343 the percentage of rainy days is less than 30%). This is attributed to the conclusion in
344 Morrison et al. [2009] who found that two-moment microphysics can produce a wider

345 spread of stratiform precipitation as a result of weaker rain evaporation rate below the
346 melting layer compared to one-moment microphysics in the stratiform region. The
347 rate of rain evaporation is associated with the difference in predicted rain size
348 distribution intercept parameter (which is larger in the stratiform region than that in
349 two-moment scheme but is specified as a constant in one-moment scheme). That is,
350 the raindrop number concentration in two-moment scheme is usually less than that in
351 one-moment scheme in the stratiform region, resulting in weaker rain evaporation rate.
352 Additionally, the representation of cloud droplet concentration is probably another
353 reason for the difference. Saleeby et al. [2010] showed an increase in aerosol
354 concentration over the East China Sea by the discrepancies in rainfall estimates
355 between the TRMM PR and TMI sensors. In CAMS scheme, similar increase of
356 droplet concentration over domain 3 (reach up to 300 cm^{-3} sometimes) will reduce the
357 autoconversion efficiency of cloud water to rain. As a result, raindrop number
358 concentration decreases, mean raindrop diameter and collision coalescence rate
359 increase, leading to high rainfall frequency during the rain formation process under
360 the condition of sufficient water vapor. Li et al [2011] also revealed that the rainfall
361 frequency increases with increasing condensation nuclei for high liquid water path
362 (LWP).

363 Table 2 shows the mean precipitation amount, percentage of rainy days, and
364 precipitation intensity (precipitation divided by percentage of rainy days) averaged
365 over domain 3. Some previous studies have focus on these characters of precipitation
366 [Dai, 2001; Sun et al., 2006]. The percentage of rainy days with precipitation

367 exceeding 0.1 mm day^{-1} from TRMM dataset is 47.4%. The R2 reanalysis and WRF
368 model outputs fall between 49.1 and 57.1%, which are a little larger than the TRMM
369 observations. The percentage of rainy days from Goddard scheme tends to be lower
370 than that from CAMS scheme as discussed above. As a result, the model precipitation
371 intensities from R2 reanalysis and WRF simulations are slightly weaker than the
372 TRMM precipitation intensity.

373 The percentage of days with heavy precipitation (exceeding 50 mm day^{-1}) is shown
374 in Figure 7. Typical summer monsoon heavy rainbands are located over the Philippine
375 Sea, South China Sea, and southeast China coast. The R2 reanalysis, limited by coarse
376 resolution and cumulus parameterization, underestimates heavy rainfall events
377 compared to the TRMM observations. The WRF downscaling simulations are
378 evidently improved than that from R2 reanalysis, especially over southeastern China
379 and South China Sea. However, CAMS scheme overestimates the frequency of heavy
380 precipitation by up to 3-6 percentage points over the Philippine Sea, resulting in larger
381 precipitation amount over there. Note that the broad feature of heavy precipitation
382 frequency follows a similar spatial pattern compared to that of the daily mean
383 precipitation (Figure 4), especially for the locations with maximum values. The
384 maximum accumulated precipitation amount is clearly attributable to the heavy
385 precipitation events.

386 To further examine the rainfall frequency distribution, the observed TRMM daily
387 precipitation in the period of May to June 2008 within the domain 3 is partitioned into
388 12 bins (only the rainy days are included), covering the first nine decile bins (0-10%,

389 10-20%, ... 80-90%) and the 90-95%, 95-99%, and 99-100% bins. In the following
390 discussions, 0-30% bin is taken as light precipitation; 30-60% bin as moderate
391 precipitation; 60-90% bin as heavy precipitation; 90-100% bin as very heavy
392 precipitation, and the top 1% as extreme precipitation.

393 In addition to the TRMM data, we also calculate the frequency distributions for
394 model assimilated R2 and WRF simulated rainfall data. The daily precipitation at
395 original grid resolution for the same period and domain from each datasets are used.
396 The calculated frequency distributions are shown in Figure 8. For light precipitation
397 especially the first percentile bin (precipitation rates between 0.1 and 0.6 mm day⁻¹),
398 the WRF simulated frequency is much higher; while the assimilated frequency in R2
399 reanalysis is lower. For moderate to heavy precipitation, the WRF simulations are
400 generally lower, and R2 reanalysis data show the opposite frequency. For the very
401 heavy precipitation, R2 reanalysis data obviously underestimate, especially the top 1%
402 extreme precipitation (great than 107.5 mm day⁻¹). The above features confirm the
403 reasoning that the R2 reanalysis data cannot resolve the physical processes and
404 mesoscale weather systems to produce extreme precipitation. The WRF simulated
405 extreme events are in good agreement with the TRMM observations due to the
406 cloud-resolving microphysics resolved in high resolution WRF model. Better
407 representation of climate extreme is a key consideration for regional climate
408 simulation, and the WRF results here show a reasonable skill and add more value to
409 the downscaling approach in reproducing the very heavy precipitation.

410 The WRF simulated precipitation frequency by the two cloud schemes in Figure 8

411 show that the CAMS scheme produce less frequency in light rains and slightly more
412 frequency in heavy rains compared with those from Goddard scheme. Note that only
413 the days with precipitation amount exceeding 0.1 mm day^{-1} are included in the
414 statistics. Li et al. [2011], using the observations at the Southern Great Plains (SGP)
415 site during the summer seasons, suggested that light rains occur less frequently and
416 heavy rains occur more frequently under polluted conditions than under clean
417 conditions. The simulated cloud droplet concentrations in CAMS scheme can
418 sometimes reach up to $\sim 300 \times 10^6 \text{ m}^{-3}$ and are higher than the common value over the
419 ocean (i.e., $\sim 50 \times 10^6 \text{ m}^{-3}$), to some extent like the real polluted conditions over NWP
420 region [Berg et al. 2008]. In addition, the features of precipitation frequency
421 distribution from R2 reanalysis are qualitatively opposite to those from WRF
422 simulations, probably due to the cloud-resolving microphysics used in WRF model
423 whereas the cumulus parameterization used in R2 reanalysis. The microphysics
424 scheme usually produces larger area of stratiform precipitation than that from cumulus
425 parameterization [Chin et al., 2010].

426 To investigate the distribution of precipitation amount, Figure 9 shows the observed
427 and simulated percentage of precipitation amount in the two summer monsoon months
428 over WNP region (Domain 3) as a function of precipitation rate. The bins used here
429 represent the light (0-30%), moderate (30-60%), heavy (60-90%), and very heavy
430 (90-95%, 95-99%, and 99-100%) precipitation, respectively. The TRMM observations
431 exhibit a broad frequency distribution with the peak between 9.9 and 38.4 mm day^{-1}
432 (the third bin, heavy rain). The WRF simulations produce slightly more light

433 precipitation than the TRMM observations because of too much light rain days
434 (Figure 8). The light precipitation contributes only about 3% of the total precipitation
435 amount although the occurrence frequency is the highest. The total precipitation
436 amount comes mainly from the heavy precipitation bin, and the R2 reanalysis
437 overestimates the contribution of heavy precipitation to the total precipitation ($\sim 53\%$)
438 because of higher occurrence frequency. In addition, the percentages for the very
439 heavy precipitation (exceeding 56 mm day^{-1} above top 5%) in R2 reanalysis decrease
440 rapidly, corresponding to the lower occurrence frequency of very heavy precipitation.
441 On the contrary, the WRF simulated extreme amount (top 1%) is slightly stronger but
442 close to the TRMM observations. The accumulated extreme precipitation amount is
443 comparable to that of the moderate precipitation (the second bin).

444 One of the main advantages of dynamical downscaling identified in previous
445 studies is about the improvement in simulating extreme events over land due to a more
446 realistic representation of topography. Here our results show a notable improvement in
447 simulated extreme precipitation over the ocean, apparently due to explicitly resolved
448 cloud microphysics with high spatial resolution. Note that some heavy precipitation
449 events over the southeast China coast are included in our analysis, but the majority of
450 very heavy precipitating events occurred over the warm NW Pacific and the rainfall
451 statistics shown in Fig. 8 and 9 is not expected to be affected.

452

453 **5. Hydrologic budgets**

454 In this section, the hydrologic budget is analyzed to further understand relevant

455 precipitation processes. We calculate the atmospheric hydrologic budget averaged
 456 over domain 3 during May to June 2008 by the following conservations equation for
 457 water vapor [Peixoto and Oort, 1983]:

$$458 \quad \frac{\partial}{\partial t} \frac{1}{g} \int_{p_s}^0 q dp + \nabla \cdot \frac{1}{g} \int_{p_s}^0 q \mathbf{V} dp = E - P \quad (1)$$

459 where q and \mathbf{V} are specific humidity and horizontal wind vector at pressure level p ,
 460 p_s is the surface pressure, the first two terms on the left hand side represent the
 461 tendency change of precipitable water and the moisture flux divergence, E and P on the
 462 right hand side are surface evaporation and precipitation. We use the 6 hourly
 463 reanalysis data and the model outputs to calculate the above budget terms.

464 Figure 10 shows the simulated daily mean moisture convergence, evaporation,
 465 precipitable water tendency, and precipitation by WRF with CAMS scheme. Results
 466 show that the spatial distribution of precipitation coincides with that of the moisture
 467 convergence, and evaporation has a near uniform distribution with a magnitude near
 468 half of the precipitation amount. This is similar to the result of Xue et al. [2004] who
 469 investigated the monsoon development over East Asia and West Africa, and found that
 470 the monsoon precipitation is related more closely to the moisture convergence field
 471 rather than surface evaporation.

472 Integration of Eq. (1) over the region specified as the domain 3 in the WRF
 473 experiments yields:

$$474 \quad MC = P - E + dW \quad (2)$$

475 Eq. (2) states the total amount of water vapor that enters the domain (MC) should be
 476 balanced with the precipitation (P) and precipitable water tendency (dW) minus

477 evaporation (E) [Wang and Yang, 2008]. Figure 11 exhibits the time evolutions of the
478 four moisture budget terms in Eq. (2) from R2 reanalysis and WRF simulations. The
479 red line denotes the residual term (MC_{res}) defined as the sum of the three terms on the
480 right-hand side of Eq. (2). Results show that the water vapor convergence in R2
481 forcing fields somewhat differs from the residual term MC_{res} (Figure 11a). This
482 imbalanced water vapor budget in the reanalysis data is mainly induced by the
483 artificial nudging process [Roads et al., 2002]. The imbalance here is small because
484 the budget is averaged mostly over the ocean relative to budget over the land surface
485 that can be made up of mountain, various vegetation etc., and cause large difference in
486 surface heating. The calculated budgets using the two WRF outputs are balanced with
487 vapor convergence (MC) in close agreement with MC_{res} (Fig. 11b and 11c). The
488 temporal mean vapor budget terms in Eq. (2) for the period of May to June 2008
489 (Table 3) show that values of evaporation in R2 reanalysis and WRF simulations are
490 similar (near 4 mm day^{-1}); however, the moisture convergence in CAMS scheme is
491 about 3 times stronger than that in Goddard scheme. Consequently, the simulated total
492 precipitation in CAMS scheme is larger than that in Goddard microphysics scheme.
493 This is more evident in Fig. 11 during the periods of heavy precipitation in the middle
494 of May and end of June, the precipitation intensity is quite consistent with the amount
495 of moisture convergence, corresponding to the strong monsoon rainbands and tropical
496 cyclone activities reported in Figure 5, indicating that the heavy precipitation events
497 are contributed mainly by the stronger moisture convergence. During less convective
498 periods, the mean evaporation contributes more to the mean precipitation amount than

499 the moisture convergence. The magnitude of mean precipitation with Goddard scheme
500 during these periods is almost the same as that of evaporation.

501 Figure 12 shows the mean moisture flux vector ($\text{m kg s}^{-1} \text{ kg}^{-1}$) at 850 hPa and the
502 corresponding moisture flux convergence fields (mm day^{-1}) averaged over May and
503 June 2008 derived from R2 reanalysis, and WRF simulations. The patterns of
504 moisture flux convergence are generally in agreement with that of daily mean
505 precipitation (Figure 4), implying that the spatial distribution of precipitation is
506 mainly decided by the moisture convergence field. Two major flows of water vapor
507 transport are evident in the region of analysis. One comes from the Bay of Bengal,
508 entering into southeastern China and the subtropical WNP region through the South
509 China Sea; the other comes from the tropical western Pacific, entering the subtropics
510 along the western edge of the WNP subtropical high. The wind direction near the
511 southern boundary in Goddard scheme (Fig. 12b) is almost easterly, resulting in less
512 water vapor transport into the domain compared to that from CAMS scheme. In
513 addition, the WRF simulations show weaker moisture convergence over the western
514 South China Sea and stronger moisture convergence over the southeastern China
515 compared with that in R2 reanalysis. But, the WRF simulations are quite different
516 over the WNP region. The moisture convergence from CAMS scheme is stronger than
517 that from Goddard scheme because of the differences in simulated wind fields.

518 Although the two WRF simulations are subject to the same boundary forcing from
519 the R2 reanalysis, the two microphysics schemes cause considerable differences in the
520 simulated location and strength of precipitation and atmospheric latent heating, which

521 in turn significantly modify the large-scale circulation. As a result, the CAMS scheme
522 produces stronger moisture convergence than the R2 reanalysis, and the Goddard
523 scheme produces weaker moisture convergence. The downscaling results suggest the
524 importance of convective heating in summer monsoon climate over the WNP region.
525 This is consistent with tropical wave dynamics that latent heat release is a dominant
526 forcing that drives the large-scale circulation [Chang et al., 1982]. So, a proper
527 representation of model microphysics is critical in simulating rainfall distribution and
528 latent heating which is as important as the large-scale dynamics governing tropical
529 waves, monsoon surges, and climate oscillations in the tropical and NW Pacific climate
530 region.

531

532 **6. Summary and conclusion**

533 Precipitation is a key climate quantity, and reducing the precipitation bias is one of
534 the major goals for improving climate simulations. In this paper, we evaluate the
535 capability of the cloud-resolving WRF via a dynamical downscaling approach, on
536 simulating regional precipitation, especially extreme precipitation events and the
537 regional hydrologic budgets over the western North Pacific. The period of study is
538 from May to June 2008, the period of transition from the onset of South China Sea
539 monsoon to the WNP summer monsoon.

540 Our analysis indicates that the R2 reanalysis data well represents the large-scale
541 characteristics of daily mean precipitation over the WNP region, but not the spatial
542 distribution of precipitation revealed in the TRMM observations dominated by extreme

543 rainfall events. This is due to the low resolution and parameterized convective
544 processes in R2 reanalysis which inadequately resolve mesoscale precipitating features
545 and smooth out the extreme events. The WRF downscaling simulations, however,
546 reasonably produce more detailed spatial distribution of daily mean precipitation as
547 reflected by higher pattern correlation coefficients and smaller pattern RMSE with the
548 TRMM observations.

549 The percentage of rainy day (exceeding 0.1 mm day^{-1}) from WRF simulations are
550 evidently improved than that from R2 reanalysis data. The CAMS scheme produces a
551 little more rainy days than that from Goddard scheme. This is attributed to the
552 two-moment microphysics in CAMS causing widespread stratiform precipitation due
553 to weaker evaporation of rainwater below the melting layer relative to the one-moment
554 microphysics in Goddard. Meanwhile, the spatial patterns of rainy days with
555 precipitation exceeding 50 mm day^{-1} from WRF simulations are similar to the spatial
556 patterns of daily mean precipitation, indicating that the maximum accumulated
557 precipitation amount is mainly contributed by heavy precipitation events. In addition,
558 the WRF simulations overestimate the frequency of light precipitation, somewhat
559 underestimate the frequency of moderate to heavy precipitation, but well represent the
560 frequency of very heavy precipitation, compared with the frequency distribution from
561 TRMM data.

562 The moisture convergence from WRF simulations balances with the sum of
563 precipitation and precipitable water tendency minus evaporation. During more
564 convective periods, the precipitation amount is primarily contributed by moisture

565 convergence. In less convective periods, the precipitation amount is more contributed
566 by evaporation. The WRF simulations with these two microphysics schemes produce
567 significantly different budget balance. Compared with the R2 budget, the moisture
568 convergence is smaller in the Goddard scheme but larger in the CAMS scheme. The
569 significant difference in simulated vapor budgets indicates the importance of resolving
570 convection in tropical monsoon region that affects the precipitation, atmospheric latent
571 heating and then the large-scale circulation.

572

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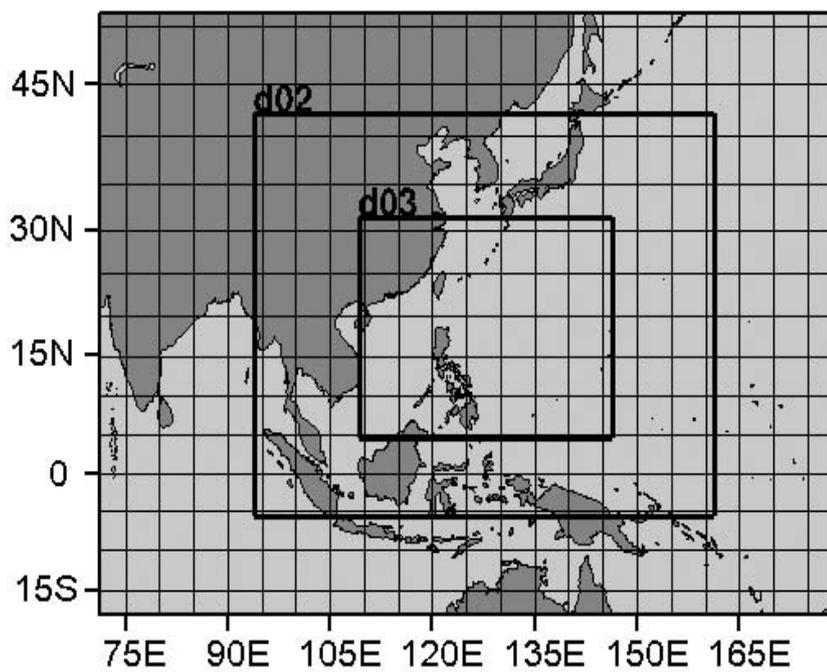
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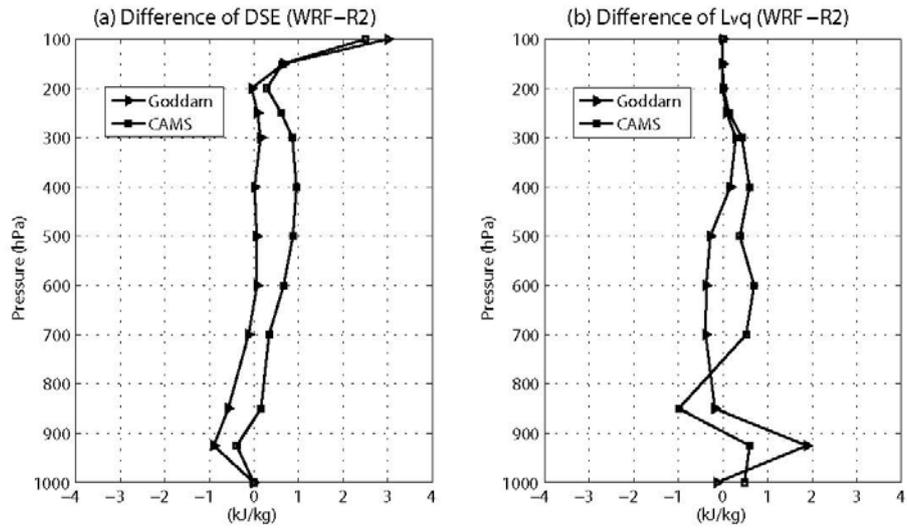
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798

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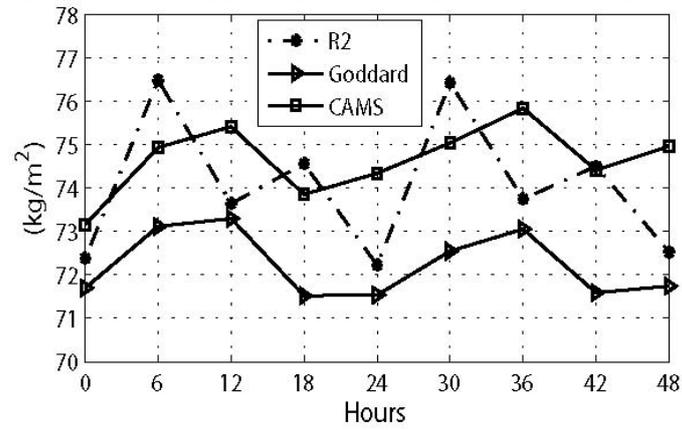


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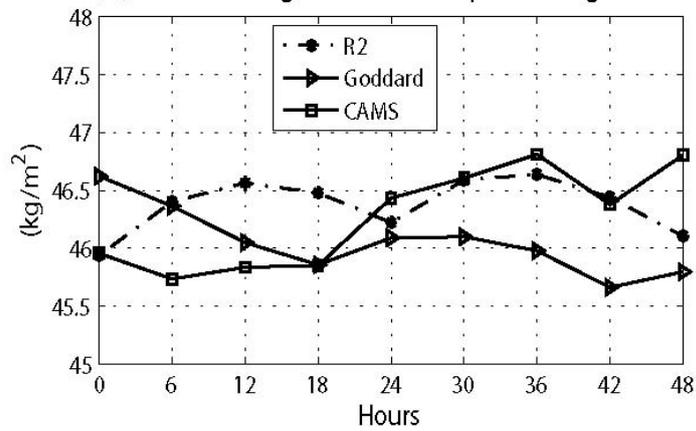
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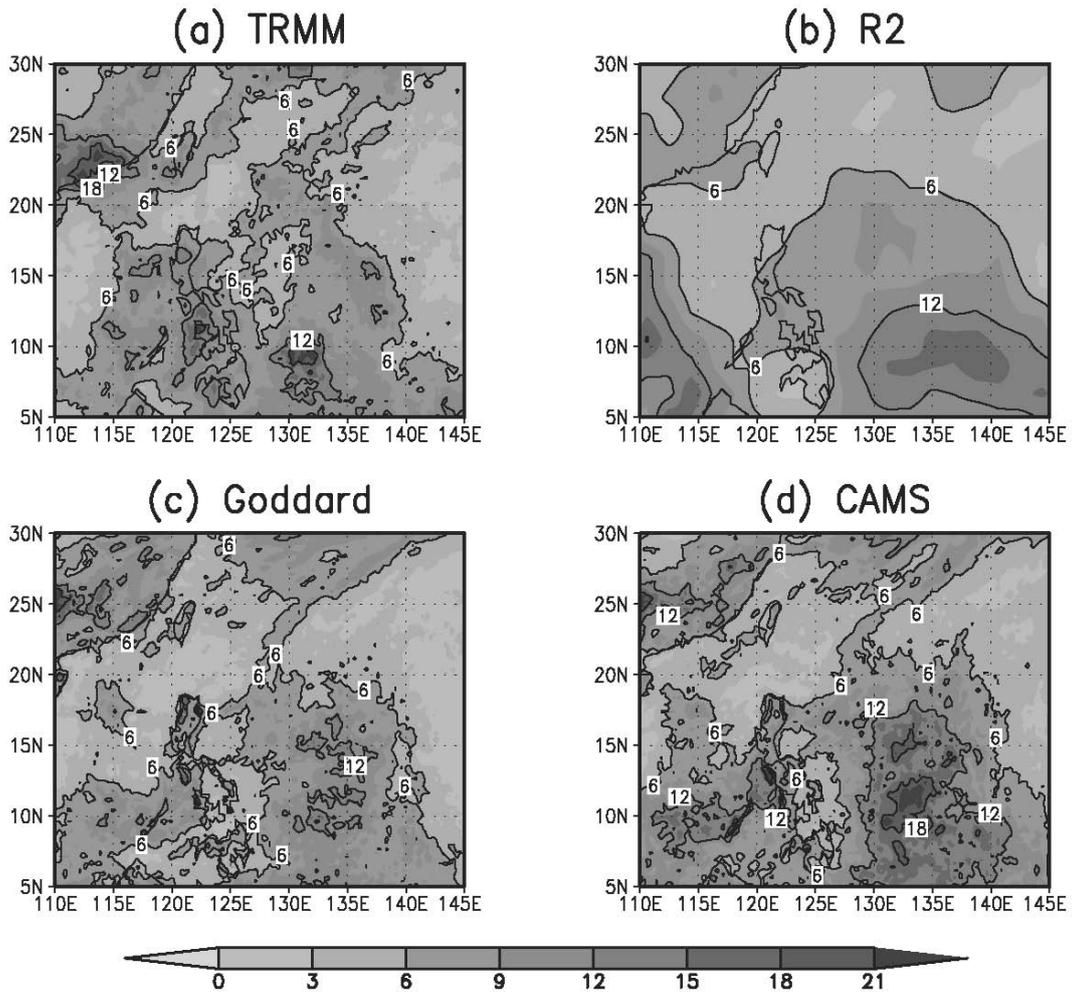


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804 Figure 3. The diurnal composites of vertically integrated (a) saturation water vapor

805 mixing ratio and (b) water vapor mixing ratio averaged over domain 3 from 30

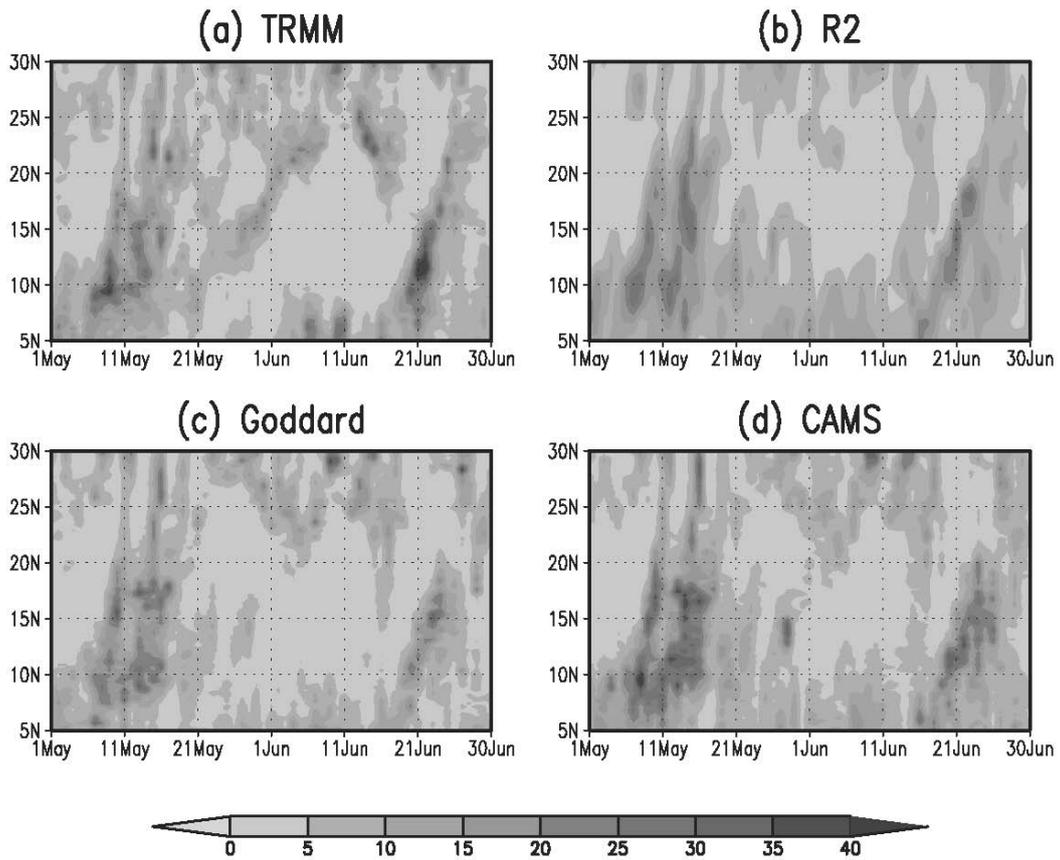
806 consecutive two-day integrations



807

808 Figure 4. Spatial distribution of the daily mean precipitation (mm day⁻¹) during May

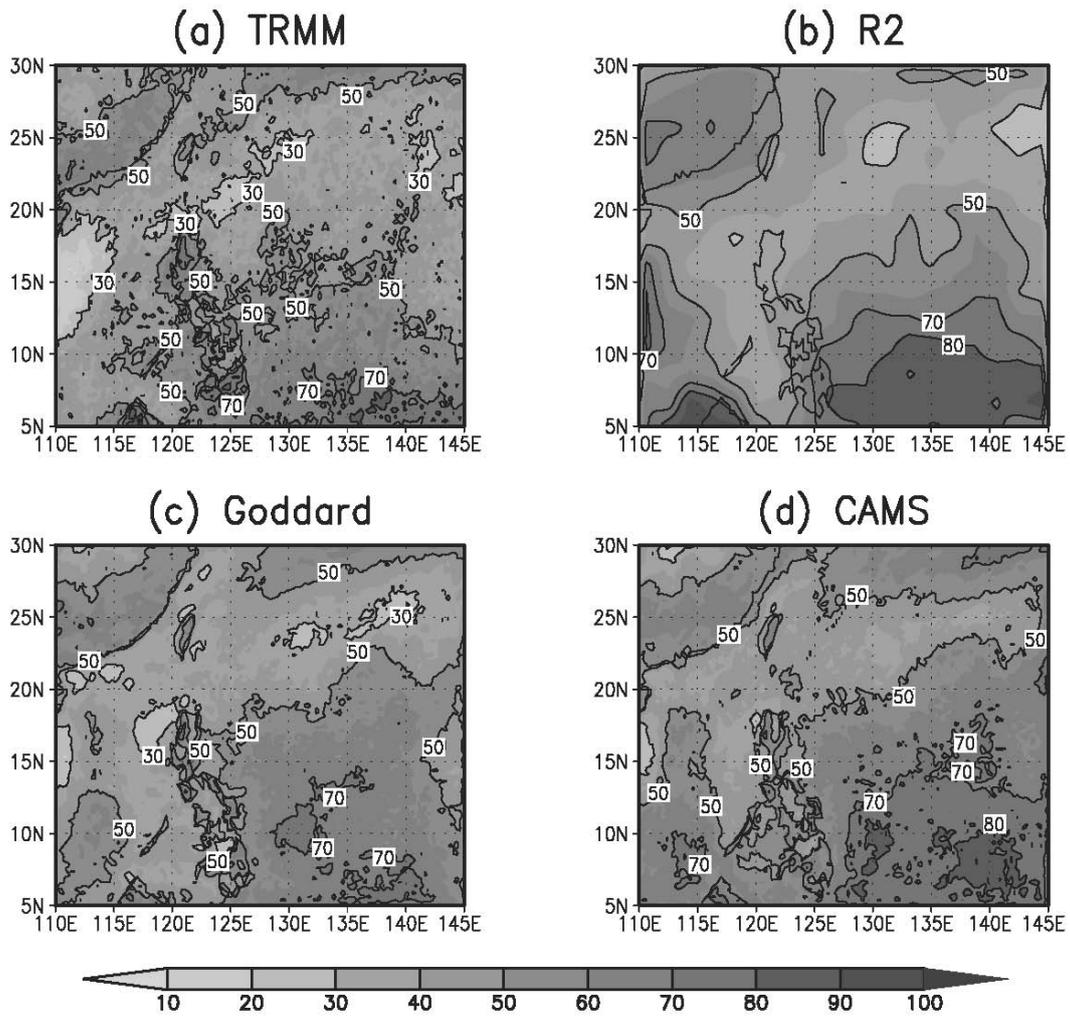
809 to June 2008 from (a) TRMM, (b) R2 reanalysis, and (c), (d) WRF simulations.



810

811 Figure 5. Precipitation (mm day^{-1}) as a function of time and latitude averaged over

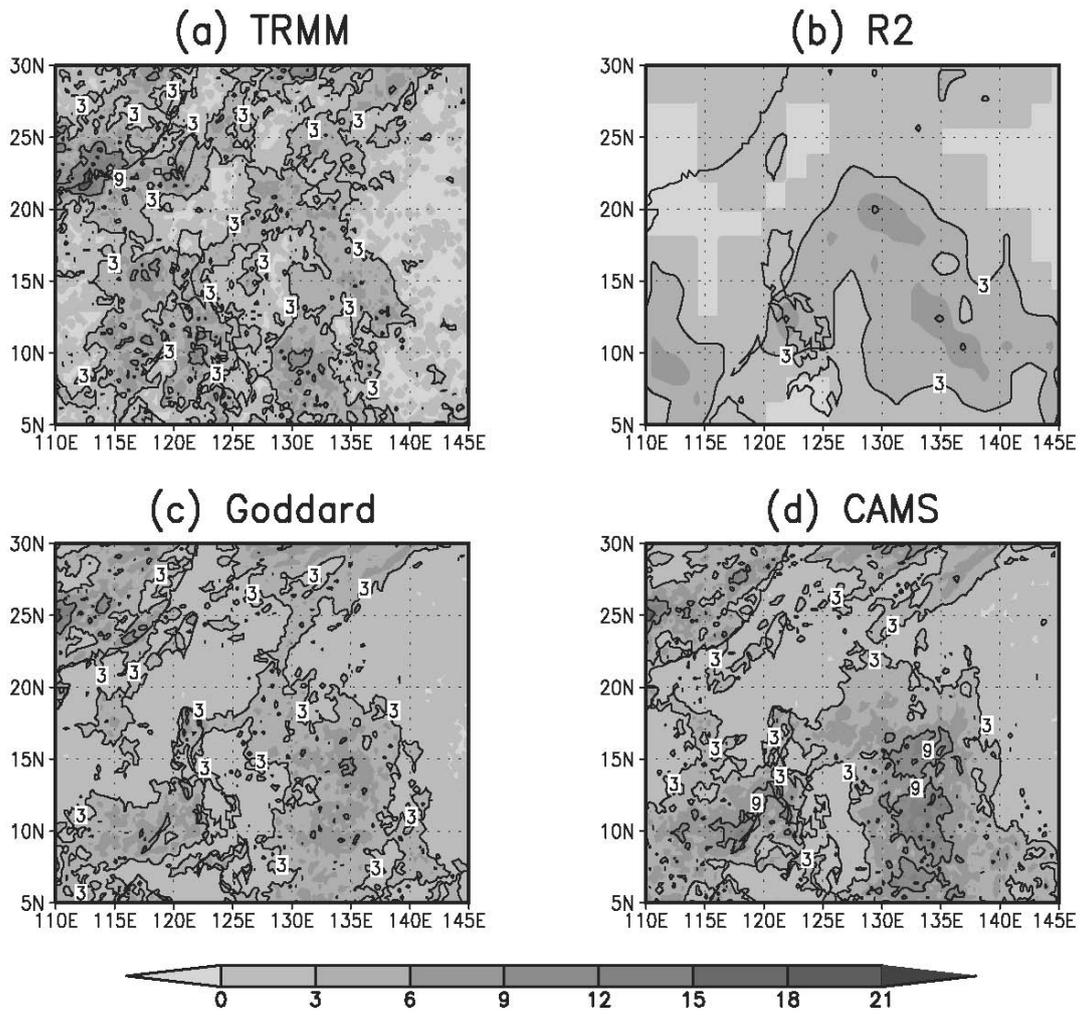
812 110° - 145° E from (a) TRMM, (b) R2 reanalysis, and (c), (d) WRF simulations.



813

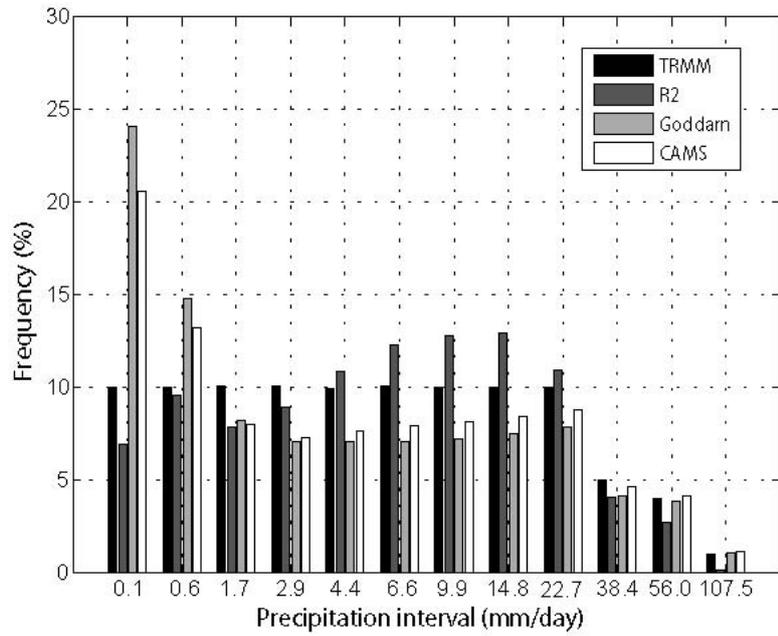
814 Figure 6. Percentage of days with precipitation rate exceeding 0.1 mm day^{-1} during

815 May to June 2008 from (a) TRMM, (b) R2 reanalysis, and (c), (d) WRF simulations.



816

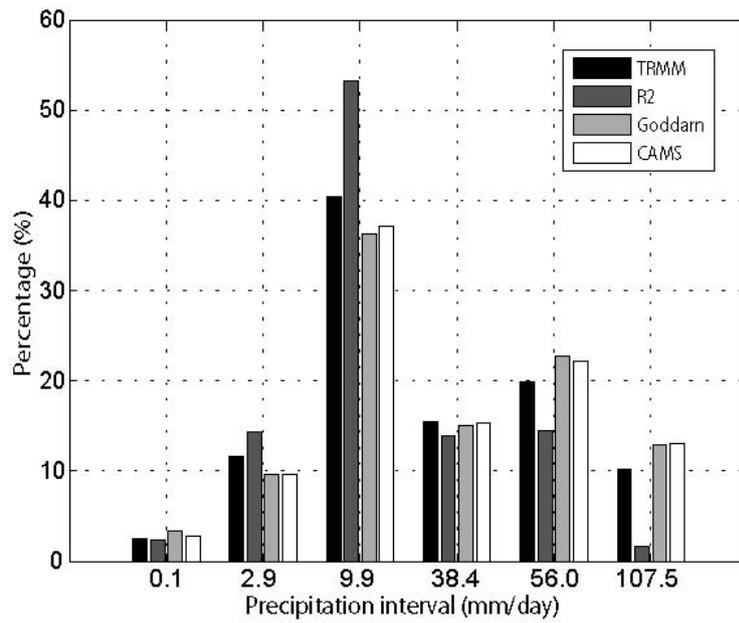
817 Figure 7. As Figure 6 but for precipitation rate exceeding 50 mm day⁻¹.



818

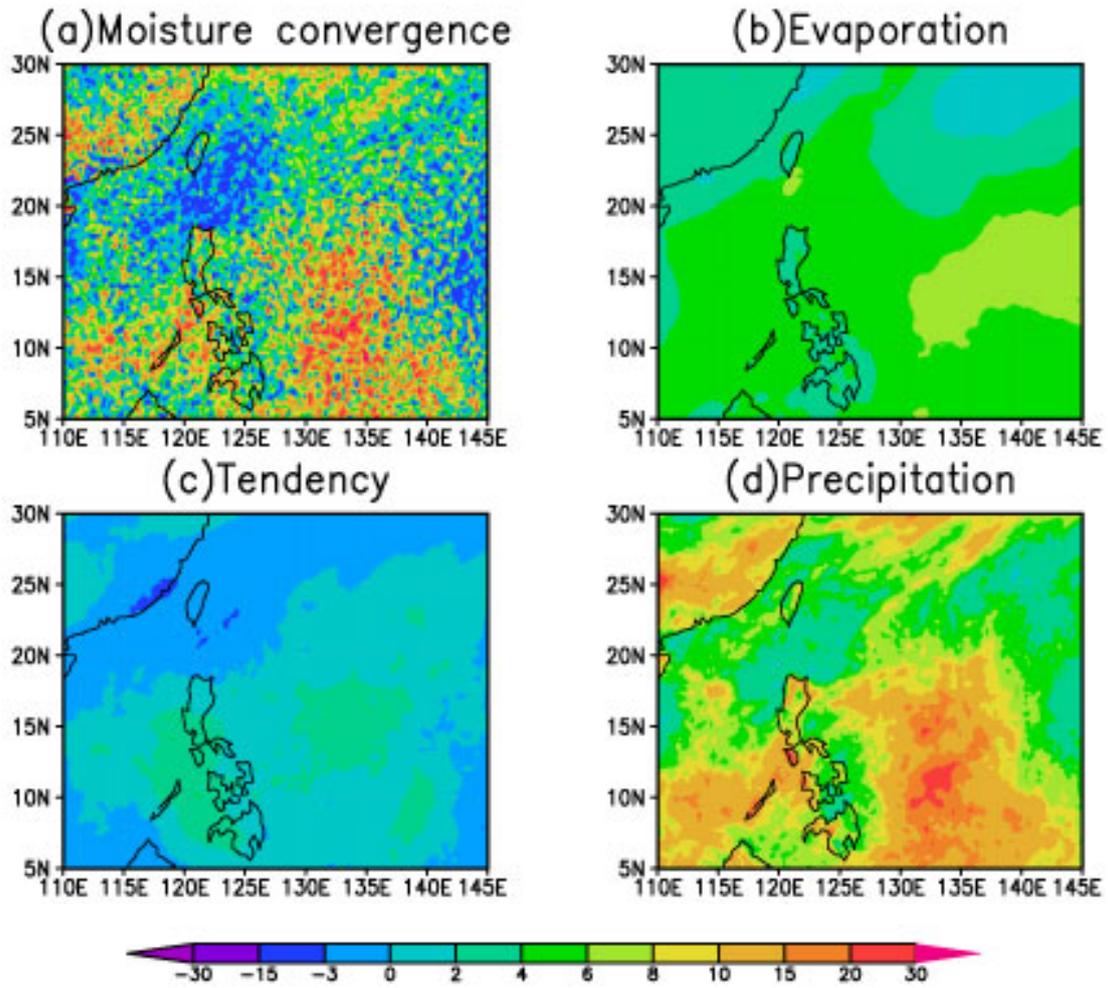
819 Figure 8. Probability distribution of observed and simulated daily precipitation at

820 different intervals over domain 3.



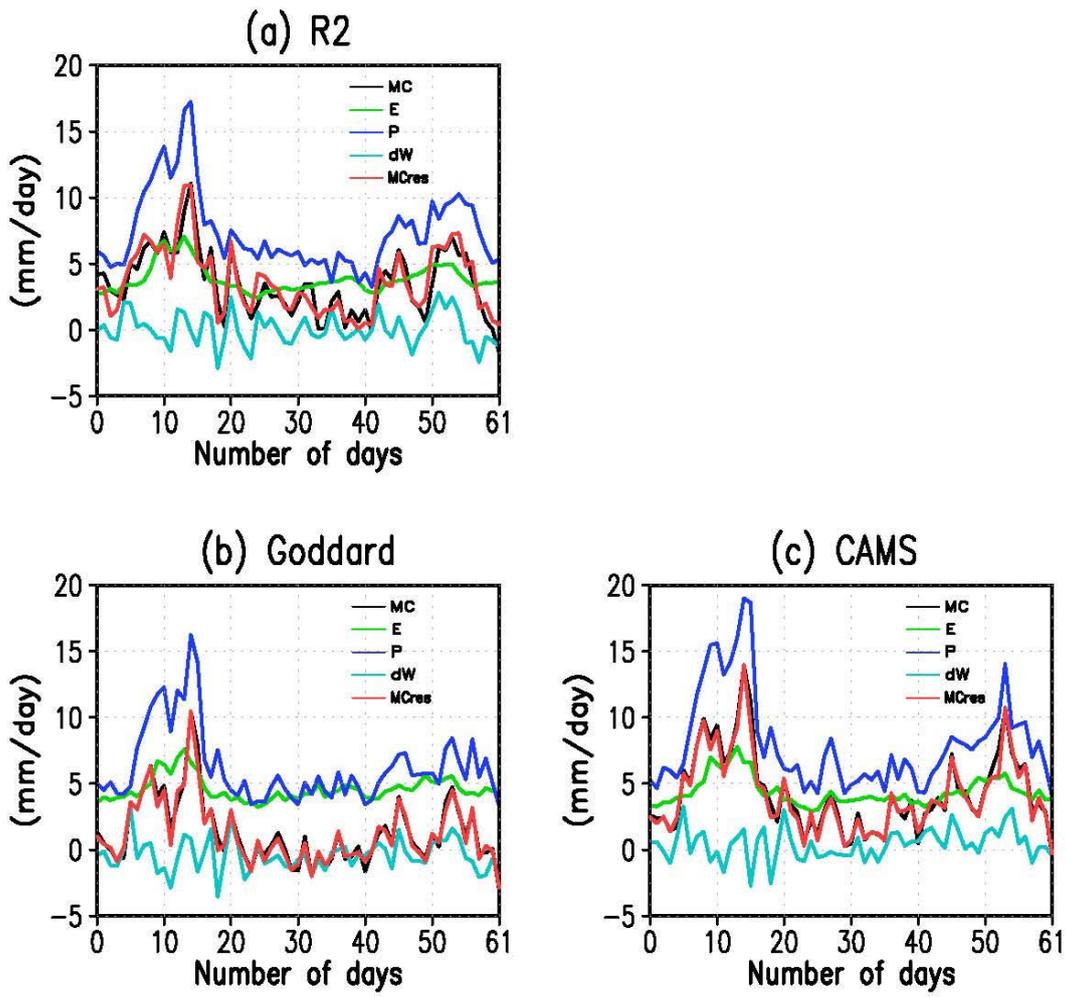
821

822 Figure 9. Percentage of observed and simulated precipitation amount as a function of
 823 precipitation rate over domain 3.



824

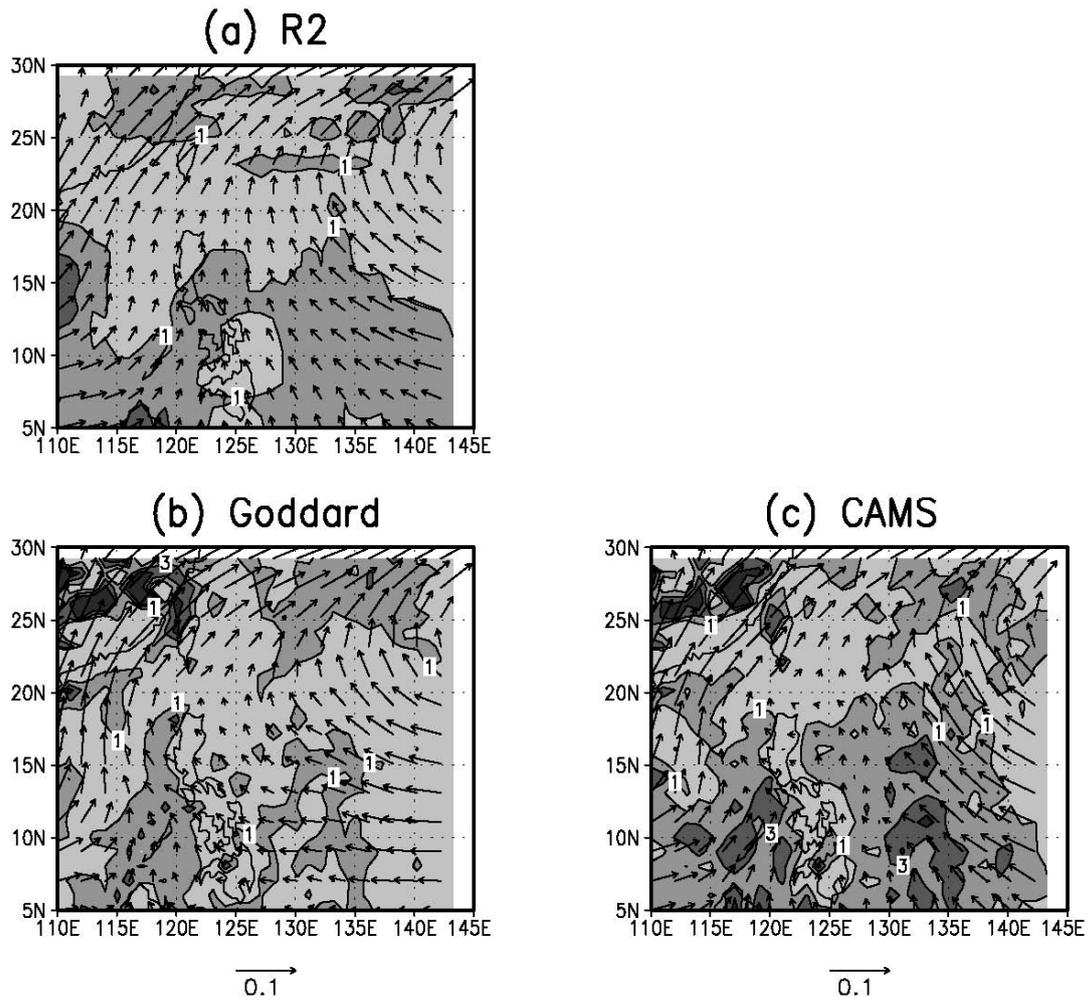
825 Figure 10. Daily mean (a) moisture convergence, (b) evaporation, (c) precipitable
 826 water tendency, and (d) precipitation (mm day⁻¹) derived from CAMS microphysics
 827 during May to June 2008.



828

829 Figure 11. Time evolution of the daily mean moisture budget averaged over domain 3

830 from (a) R2 reanalysis, (b) Goddard, and (c) CAMS simulations.



831

832 Figure 12. Mean 850 hPa moisture flux vector ($\text{m kg s}^{-1} \text{kg}^{-1}$) with associated moisture

833 convergence fields (mm day^{-1}) averaged over May and June 2008 from (a) R2

834 reanalysis, (b) Goddard, and (c) CAMS simulations.

835 Table 1. Area-averaged daily mean precipitation (mm day^{-1}), pattern RMSE (mm day^{-1})
 836 and pattern correlation coefficients between the observed and simulated daily mean
 837 precipitation shown in Figure 4.

	TRMM	R2	Goddard	CAMS
Mean	7.03	7.38	6.24	8.01
Spatial RMSE	-	4.20	3.26	4.00
Spatial correlation	-	0.26	0.53	0.48

838 Table 2. Area-averaged daily mean precipitation (mm day^{-1}), percentage of rainy days
839 (%) and precipitation intensity (mm day^{-1}).

	TRMM	R2	Goddard	CAMS
Mean	7.03	7.38	6.24	8.01
Rainy days	47.4	55.6	49.1	57.1
Intensity	14.8	13.3	12.7	14.0

840 Table 3. The daily mean hydrologic budget terms averaged over domain 3 during May
841 to June 2008.

	MC	E	P	dW
R2	3.03	3.86	7.38	0.05
Goddard	1.31	4.58	6.26	-0.45
CAMS	4.26	4.38	8.01	0.42

842