

Assessing precipitation over the Amazon basin as simulated by a storm-resolving model

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November 25, 2022

Abstract

In this study we investigate whether a better representation of precipitation in the Amazon basin arises through an explicit representation of convection and whether it is related to the representation of organized systems. In addition to satellite data, we use ensemble simulations of the ICON-NWP model at storm-resolving (2.5-5.0 km) scales with explicit convection (E-CON) and coarse resolutions, with parameterized convection (P-CON). The main improvements in the representation of Amazon precipitation by E-CON are in the spatial pattern of precipitation, the distribution of precipitation intensity and the spatial distribution in the diurnal cycle. By isolating precipitation from organized convective systems (OCS), it is shown that many of the well simulated precipitation features in the Amazon arise from the distribution of these systems. The simulated and observed OCS are classified into 6 clusters which distinguish nocturnal and diurnal OCS. While the E-CON ensembles capture the OCS, especially their diurnal cycle, their frequency is reduced compared to observations. Diurnal clusters are influenced by surface processes such as cold pools, which aid to the propagation of OCS. Nocturnal clusters are rather associated with strong low-level easterlies, possibly related to the Amazonian low-level jet. These particular environmental conditions provide insights on the processes that are important for OCS in the Amazon and should be further improved.

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2 **simulated by a storm-resolving model**

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6 **Key Points:**

- 7 • The explicit representation of convection and organized convective systems (OCS)
8 enable improvements in the simulation of Amazon rainfall.
- 9 • Surface processes influence the propagation of diurnal OCS and strong low-level
10 easterlies are related to the occurrence of nocturnal OCS.
- 11 • Outstanding biases show insensitivity to two fold refinement in horizontal mesh,
12 indicative of the importance of much smaller scale processes.

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Abstract

In this study we investigate whether a better representation of precipitation in the Amazon basin arises through an explicit representation of convection and whether it is related to the representation of organized systems. In addition to satellite data, we use ensemble simulations of the ICON-NWP model at storm-resolving (2.5 km to 5.0 km) scales with explicit convection (E-CON) and coarse resolutions, with parameterized convection (P-CON). The main improvements in the representation of Amazon precipitation by E-CON are in the spatial pattern of precipitation, the distribution of precipitation intensity and the spatial distribution in the diurnal cycle. By isolating precipitation from organized convective systems (OCS), it is shown that many of the well simulated precipitation features in the Amazon arise from the distribution of these systems. The simulated and observed OCS are classified into 6 clusters which distinguish nocturnal and diurnal OCS. While the E-CON ensembles capture the OCS, especially their diurnal cycle, their frequency is reduced compared to observations. Diurnal clusters are influenced by surface processes such as cold pools, which aid to the propagation of OCS. Nocturnal clusters are rather associated with strong low-level easterlies, possibly related to the Amazonian low-level jet. These particular environmental conditions provide insights on the processes that are important for OCS in the Amazon and should be further improved.

Plain Language Summary

The Amazon basin is a relevant element of the Earth system since it influences the global water and carbon cycle, as well as it constitutes a unique ecosystem. Over this important region, conventional climate models do not simulate basic features of rainfall given their inability to resolve this physical process due to their coarse spatial resolution. In this study, we use high-resolution simulations that allow an explicit representation of such physical process (moist convection) and compare them with a set of coarse-resolution simulations and observations. We find that improvements in the representation of Amazon rainfall, such as the distribution of light and high intensity rain rates, as well as the spatial variability of the diurnal cycle, are explained by the explicit representation of moist convection. Moreover, these improvements arise from the representation of big and organized systems that produce intense rainfall (OCS). We find that particular environmental conditions are associated with the OCS according to their time

of occurrence. Diurnal OCS are mainly influenced by interactions with the surface, while nocturnal OCS are related to strong low-level winds.

1 Introduction

The Amazon basin is the largest rainforest in the Earth and of great relevance for the global hydro-climate and biodiversity (Marengo, 2006; Phillips et al., 2008). It is also a region, like many in the tropics, where climate model precipitation biases are both large and systematic. These biases are evident in every aspect of the representation of precipitation, from its spatial and temporal distribution, to its intensity and form. Models systematically have too little precipitation over the northern Amazon (e.g., Yin et al., 2013; Fiedler et al., 2020). The diurnal cycle is characterized by a too early precipitation peak (Betts & Jakob, 2002; Tang et al., 2021) and evidence of convective organization (Mapes & Neale, 2011), which has been estimated to account for up to 50% of the total Amazon rain (Feng et al., 2021), is effectively absent. In this study, we use kilometer-scale "storm-resolving" simulations over large domains to assess the degree to which they reduce these biases and the extent to which this depends on the explicit representation of organized convective systems. In doing so our premise is that convective features which are not improved, or for which remaining biases show no clear sign of improvement with increases in resolution, are indicative of an important role for non-convective, e.g., cloud microphysical, small (sub hectometer) scale mixing, or land-surface processes.

The distinguishing characteristic of storm-resolving models is that they explicitly represent the transient dynamics of convective storm systems, whose length-scales are commensurate with the depth of the troposphere (Satoh et al., 2019). Representing these features become possible at grid spacings of 5 km to 10 km although there is considerable evidence that convection is increasingly distorted as grid spacings increase above 1 km to 2 km. Nonetheless, the ability to represent convective entities as geometric objects that interact dynamically with their environment, and are governed by the correct physical relations (laws of motion) seems to explain why even on 5 km to 10 km grid meshes, an explicit representation of convection leads to more physical representations of convection than what is possible using convective parameterization (e.g., Love et al., 2011; Birch et al., 2015). In recent years, storm-resolving models have shown systematic improvements in representing precipitation, albeit to a degree that seems to vary from place to place. For instance, Arnold et al. (2020) found regional differences in the mean pre-

76 precipitation of a 40-day global simulation, where precipitation is overestimated over Africa
77 but underestimated over the Great Plains in North America. While the shortness of the
78 simulations (40 days) and the remote influence of larger-scale biases might explain this
79 discrepancy, they also found that precipitation tends to peak earlier than observations
80 over regions dominated by local thermodynamic forcing; whereas the largest improve-
81 ments were found in regions where the diurnal cycle is driven by non-local propagating
82 convection.

83 Although storm-resolving models overcome the long-standing "drizzle" problem of
84 convective parameterizations (Stephens et al., 2010), they still disagree in the represen-
85 tation of high intensity precipitation rates ($>80 \text{ mm d}^{-1}$), which is strongly overestimated
86 (Becker et al., 2021) in some models, and apparently underestimated in others (Arnold
87 et al., 2020; Judt & Rios-Berrios, 2021). High intensity precipitation can be related to
88 organized convective systems which we expect storm-resolving models to better repre-
89 sent as compared to models dependent on parameterized convection (e.g., Stevens et al.,
90 2020). How much improvements in the representation of precipitation relate to the rep-
91 resentation organized convection is not evident and has not been investigated yet.

92 A few studies have begun evaluating the representation of precipitation over the
93 Amazon basin using global storm-resolving models. For example, (Inoue et al., 2021) com-
94 pared the semi-diurnal cycle of precipitation with observations for a 5-day period at 3.5 km
95 grid spacing. They found that the model captures the semi-diurnal variation of precip-
96 itation in the Amazon basin but it tends to overestimate their amplitudes, especially the
97 second peak during the early morning. Arnold et al. (2020) also analyzed a set of global
98 simulations and found a larger simulated amplitude than observed at a reduced grid spac-
99 ing (3.5 km). However, in contrast to Inoue et al. (2021), their model did not capture
100 the phase of the precipitation diurnal cycle in the Amazon.

101 For the most part, storm-resolving model simulations at the regional scale have not
102 been able to look at precipitation over the Amazon in its entirety. For instance, Santos
103 et al. (2019) used a small domain enclosing the city of Manaus and a grid scale of about
104 780 m. They found that seasonal floods can enhance the intensity of river circulations
105 during daytime and hence convection. Over the eastern Amazon at a grid spacing of 1.5 km,
106 Herbert et al. (2021) analyzed the impact of biomass burning on the diurnal cycle of pre-
107 cipitation. They found that convection is suppressed in the afternoon but enhanced overnight

108 due to aerosol-radiation interactions. Another recent study by Tai et al. (2021), inves-
109 tigated the influence of data assimilation on regional modeling of Amazon precipitation.
110 They performed a 30-day simulation at 4 km grid spacing and focused the analysis on
111 the central Amazon. Their study highlights the improved representation of spatial vari-
112 ability in the precipitation diurnal cycle in contrast to a standard climate model. This
113 feature is related to the representation of organized convective systems which are absent
114 in models reliant on convective parameterization.

115 In this study we perform storm-resolving simulations with the ICON model over
116 a large domain to study the representation of precipitation over the Amazon. In con-
117 trast to previous regional modeling studies, we focus on the Amazon basin in its entirety
118 and, unlike month-long simulations with global models, we perform an ensemble of 30-
119 day simulations at 2.5 km and 5 km grid-spacing. Simulations are performed during March
120 as this is the month with the largest convective activity (e.g., Rehbein et al., 2018). For
121 this period we document the ability of storm-resolving simulations to capture the multi-
122 faceted properties of precipitation as observed over the Amazon, in comparison with a
123 model that arguably uses the most efficient, and certainly well calibrated, statistical rep-
124 resentation of convection, i.e., that developed by Bechtold (2017) for the Integrated Fore-
125 cast System of the European Centre for Medium-range Weather Forecasts. We especially
126 focus on the role of organized convection in improving the representation of precipita-
127 tion and the extent to which this is coupled to particular environmental conditions. By
128 using two resolutions we further infer to what extent remaining deficits in the represen-
129 tation of precipitation are likely to be improved by modest (factor of 2) refinements in
130 resolution. This question becomes interesting in light of proposals to develop climate in-
131 formation systems based on global models with grid meshes of roughly 1 km (Slingo et
132 al., 2022) as it helps identify the problems that km-scale global models are likely to solve,
133 and those whose solution might require improvements in the representation of processes
134 that remain unresolved, or severely distorted, even on global km-scale meshes.

135 **2 Data and methodology**

136 **2.1 Observations**

137 We use the Climate Prediction Center Morphing Method (CMORPH; Xie et al.,
138 2017) dataset for the period from 2010 to 2019. This product estimates precipitation based

139 on passive microwave instruments. The main advantages of CMORPH data are its high
140 temporal (30min) and spatial (8 km) resolutions. Previous studies have also validated
141 its good performance over the Amazon region (e.g., Janowiak et al., 2005). We also com-
142 pared the analysis with other high-resolution datasets and similar results were obtained;
143 therefore we chose the CMORPH data.

144 **2.2 CMIP6**

145 We use simulations from the Coupled Model Inter-comparison Project: Phase 6 (CMIP6;
146 Eyring et al., 2016). Multi-model ensemble means are used from the historical simula-
147 tions of the 21th century (2000-2014) and are the same used in Fiedler et al. (2020). We
148 use daily and 3-hourly data available from 14 and 13 models, respectively. Simulations
149 were spatially interpolated to the common T63 grid (about 180 km), the native grid of
150 MPI-ESM low-resolution configuration. For a detailed list of the models, the reader is
151 referred to the supplementary material of Fiedler et al. (2020).

152 **2.3 ICON-NWP**

153 We use the Icosaedral Nonhydrostatic (ICON) atmospheric model (Zängl et al., 2015)
154 in the numerical weather prediction (NWP) configuration. Among the applied physical
155 parameterizations by this model, the parameterization of moist convection is only used
156 for the coarser grid spacing in our experiments. It consists of a bulk mass-flux scheme
157 (Bechtold, 2017), which is one of the latest implementations in the NWP of European
158 meteorological services. Parameterizations common to all simulations are given for pro-
159 cesses such as radiation, microphysics and turbulence as described in Zängl et al. (2015).
160 Also, the ICON-NWP model uses the multi-layer land-surface scheme TERRA (Heise
161 et al., 2006).

162 As initial conditions for the simulations we use the operational analysis data from
163 the European Centre for Medium-Range Weather Forecasts (ECMWF) - Integrated Fore-
164 cast System (IFS), and from the Hadley Centre Sea Ice and Sea Surface Temperature
165 Center (HadISST; Rayner et al., 2003) for SST. Grids and external parameters (e.g. land
166 properties, topography) are retrieved from the Online Grid Generator tool from the Ger-
167 man Meteorological Service (DWD).

168 **2.3.1 Experimental set-up**

169 We conduct a set of simulations using the same approach as Paccini et al. (2021).
170 Global simulations, at 40 km grid spacing (P-CON simulations), serve as initial and bound-
171 ary conditions to the one-way nested domains at finer grid spacing. The three inner do-
172 mains have the convective parameterization switched off (E-CON simulations) and com-
173 prise the same regions as described in Paccini et al. (2021). The horizontal resolution
174 is successively increased from 20 km to 10 km and to 5 km, with the finest grid spacing
175 covering the tropical Atlantic sector (85°W-25°E; 25°S-25°N). In all domains the verti-
176 cal resolution includes 90 levels, with the model top at 75 km.

177 We start 8 simulations at the beginning of March, with different atmospheric states
178 but with the same fixed sea surface temperature (SST), which does not vary over time.
179 Simulations are integrated for 40 days and the analysis is performed over the last 31 days,
180 representing the simulation of March.

181 We conduct another set of simulations using an updated version of ICON (v2.6.01)
182 with an additional inner domain, at a grid spacing of 2.5 km, that bounds the region: 81°W-
183 36°W; 21°S-11°N. Given the high computational demands, only 2-member simulations
184 are performed.

185 In our analysis we compare the 8-member ensemble of P-CON and E-CON at 40 km
186 and 5 km, respectively, with the 2-member ensemble of E-CON at 2.5 km. Although from
187 different ensembles, the E-CON simulations at 2.5 km and 5 km lead to the same results
188 as those E-CON at 2.5 km and 5 km from the 2-member ensemble. We present then re-
189 sults of the 8-member E-CON simulations at 5 km due to more robust statistics.

190 All data and simulation outputs are regridded to the resolution of the P-CON ex-
191 periments (about 40 km) except for the CMIP6 ensemble which keeps the grid spacing
192 of about 180 km. The CMIP6 data only serves as a reference of how state-of-the-art cli-
193 mate models, representing the average convective parameterizations, simulate Amazon
194 precipitation.

3 Representation of precipitation

3.1 Geographic distribution

One of the basic metrics when evaluating the representation of rainfall is the mean amount of precipitation, and its spatial pattern. The prevailing bias in most climate models is the underestimation of rain in the Amazon, especially during the wet season (Fiedler et al., 2020). Spatially, the bias shows up as enhanced rain over the eastern region of Brazil and insufficient rain in the central Amazon (Fig. 1, e). This is a bias that does not appear to be related to a poor representation of SST patterns in coupled models, as it has also been documented in simulations using prescribed SST (Richter & Xie, 2008).

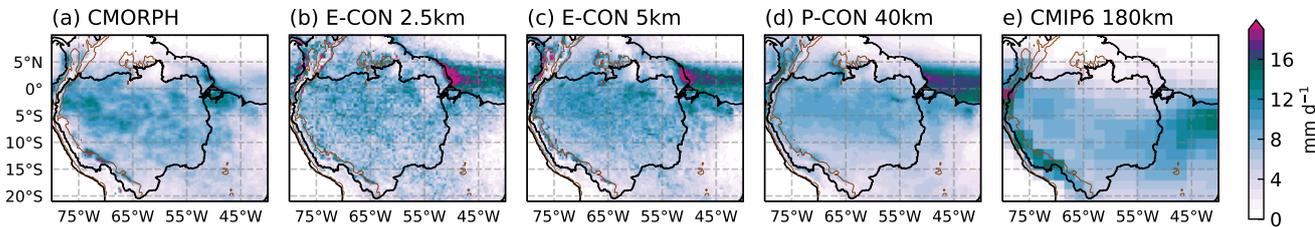


Figure 1. Mean precipitation in March from (a) CMORPH observations, simulations with explicit (E-CON) convection at (b) 2.5 km, (c) 5 km, parameterized convection (P-CON) at (d) 40km and the (e) CMIP6 multi-model ensemble mean. Data and output simulations are regridded to 40km except for CMIP6 models which were interpolated to a common grid of about 180km and only serves as a reference. The Amazon basin is defined as black contours and the topography at 1000m, in brown contours.

Both E-CON and P-CON display a better representation of the mean spatial pattern compared to the CMIP6 ensemble, meaning more rain over the central Amazon and less over eastern Brazil (Fig. 1, b, c, d). However, it still appears that the simulated precipitation is underestimated compared to the observed climatology. This can be partly explained by the simulated broader precipitation band with enhanced rainfall north of the Amazon in both E-CON and P-CON, probably related to the invariable SST used in the simulations. As a result, less precipitation in E-CON and P-CON than CMORPH is observed south of 5°S. In the case of the P-CON ensemble, the spatial distribution is more uniform, with no regions having precipitation rates larger than 12 mm d⁻¹. The E-CON ensembles do show sub-regions with larger mean values, similar to CMORPH,

214 but rainfall over parts of the western Amazon is still underestimated. This character-
 215 istic appears insensitive to modest changes in the grid spacing, as evidenced by the sim-
 216 ilarity between the 2.5 km and 5 km E-CON ensembles (Fig. 1, b, c).

217 A more localized feature, which appears sensitive to the treatment of convection,
 218 is the coastal precipitation over the northeastern coast of Brazil. Simulations with pa-
 219 rameterized convection (P-CON and CMIP6) show a lack of precipitation in this region,
 220 a bias that is not evident in the E-CON ensembles. Having an adequate representation
 221 of the coastal precipitation is thought to be important for the Amazon, due to organized
 222 convective systems that originate there and propagate inland (e.g., Greco et al., 1990).
 223 Improvements in the representation of coastal precipitation with explicit convection might
 224 be related to a better representation of breeze circulations and/or the transition from
 225 shallow to deep convection.

226 A quantitative comparison is presented in Tab. 1. Precipitation is averaged over
 227 the Amazon basin and the continental region comprised by 20°S-10°N; 80°W-38°W. Even
 228 though the differences among simulations are relatively small ($<1 \text{ mm d}^{-1}$), this anal-
 229 ysis suggests that the E-CON simulations better match the observations, increasingly
 230 so with finer grid spacing, and in regions of less orographic relief (regions below 1000 m
 231 above sea-level). The E-CON ensembles differ from observed values by less than 0.35 mm d^{-1}
 232 while precipitation biases of the P-CON simulations are nearly twice as large ($>0.5 \text{ mm d}^{-1}$).

Table 1. Averaged precipitation over the Amazon Basin (AB) and the ratio of Amazon and tropical South America (SA, 20°S-10°N; 80°W-38°W) rain rates. Values in parentheses are the averages over regions where topography is below 1000 m. For these calculations, observations and output simulations were spatially interpolated onto the CMIP6 grid (180 km).

Dataset	Mean precipitation AB (mm d^{-1})	Ratio AB/SA
CMORPH	7.86 (8.07)	1.28
E-CON 2.5km	7.71 (7.88)	1.21
E-CON 5km	8.19 (8.42)	1.19
P-CON 40km	7.33 (7.52)	1.17
CMIP6 180km	7.82 (7.41)	1.08

233 Comparing the ratio between Amazon precipitation and the tropical continent as
 234 a whole, both E-CON and P-CON display a ratio of about 1.2, similar to observations,
 235 whereas the CMIP6 ensemble shows a value closer to 1. This is related to the enhanced
 236 precipitation over high topography and over the eastern coast of Brazil in the CMIP6
 237 ensemble. Although the improvements are small, in all measures the most highly resolved
 238 E-CON simulations are closest to the observations.

239 Some aspects of the simulations show less indication of improving with a reduc-
 240 tion of the grid spacing at storm-resolving scales. Whilst all simulations with explicit
 241 convection do a fair representation, one might expect a better performance for the 2.5 km
 242 mesh simulations as compared to those with a 5.0 km mesh. For instance, along the east-
 243 ern flank of the Andes (from 10°S - 17°S), the Amazon comprises some of the rainiest
 244 places in the region, exhibiting features known as "precipitation hot spots" (e.g., Chavez
 245 & Takahashi, 2017). The E-CON ensembles exhibit a similar zonal gradient that max-
 246 imizes eastward; however not as prominently as is seen in observations. The origin of such
 247 precipitation hot-spots is not very clear, but it was found that they comprise convective
 248 and stratiform rain (Chavez & Takahashi, 2017). The results suggest that the represen-
 249 tation of these precipitation maxima may depend on yet smaller scale orographic fea-
 250 tures, as a microphysical origin of such localized features is difficult to rationalize. .

251 **3.2 Frequency and intensity**

252 The E-CON ensembles show a notable improvement in the estimated frequency and
 253 distribution of precipitation intensity in the Amazon basin (Fig. 2). The frequency of
 254 daily precipitation follows the spatial pattern of the mean precipitation (Fig. 1), featur-
 255 ing regions where it rains up to 80 % of the days in E-CON and observations (Fig. 2, a,
 256 b and c). The E-CON ensembles also distinguish more rain frequency over land areas
 257 than rivers, such as the Amazon river mouth and the Tapajos river (Fig.2 b, c), although
 258 details are smoothed by the interpolation to the common analysis grid.

259 A very different picture is displayed by simulations with parameterized convection,
 260 as P-CON shares the biases of the CMIP models, which tend to overestimate the fre-
 261 quency of light rain (Stephens et al., 2010) regardless of the spatial resolution (Fig. 2
 262 d,e). Regions where the mean precipitation is greater or equal than 5 mm d⁻¹ (Fig. 1)

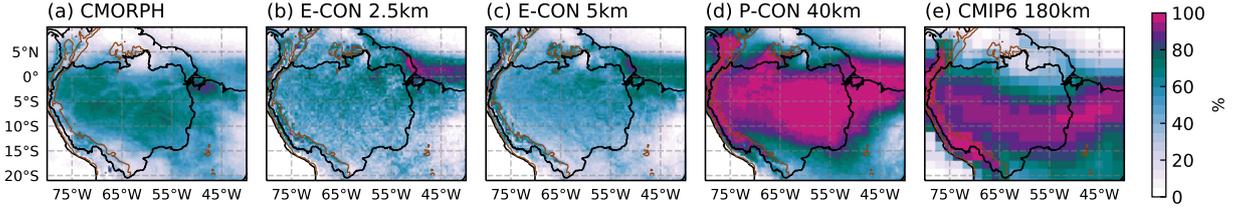


Figure 2. Frequency (%) of daily precipitation greater than 1mm d^{-1} in March from (a) CMORPH observations and simulations with explicit (E-CON) convection at (b) 2.5 km, (c) 5 km, parameterized convection (P-CON) at (d) 40 km and the (e) CMIP6 multi-model ensemble mean. Data is regridded to 40 km except for CMIP6 models which were interpolated to a common grid of about 180km and only serves as a reference. The Amazon basin is defined as black contours and the topography at 1000m, in brown contours.

263 show a frequency greater than 90 % to 95 %, indicating that the mean precipitation amount
 264 is related to the persistence of rainy days.

265 To have a broader view of the frequency spectra, Figure 3 displays the distribu-
 266 tion of precipitation intensity over the Amazon basin. The E-CON ensembles show an
 267 important improvement in the representation of this precipitation feature as compared
 268 to simulations with parameterized convection and in agreement with studies focused on
 269 different regions (e.g., Holloway et al., 2012; Becker et al., 2021; Judt & Rios-Berrios,
 270 2021). This improvement is evident across the E-CON ensembles, which suggests that
 271 it is determined by the treatment of convection rather than the details of the spatial res-
 272 olution and the experimental set-up (global versus nested, not shown). In a recent com-
 273 parison study, Judt and Rios-Berrios (2021) showed that simulations with full convec-
 274 tive parameterization run at about 4 km grid spacing displayed the same distribution of
 275 precipitation intensity as those at 100 km.

276 Differences in the intensity spectrum are most evident in two intensity intervals.
 277 First, the interval between 2 mm d^{-1} to 20 mm d^{-1} (light-to-moderate rain) occurs more
 278 frequently, with a clearly preferred intensity in simulations with parameterized convec-
 279 tion. Observations and the E-CON ensembles show a flatter distribution, and less fre-
 280 quent rainfall in this intensity interval as a whole. The second intensity interval covers
 281 precipitation rates greater than 25 mm d^{-1} (high intensity rain). As compared to obser-
 282 vations and to E-CON, these high-intensity rain events are much rarer in P-CON. The

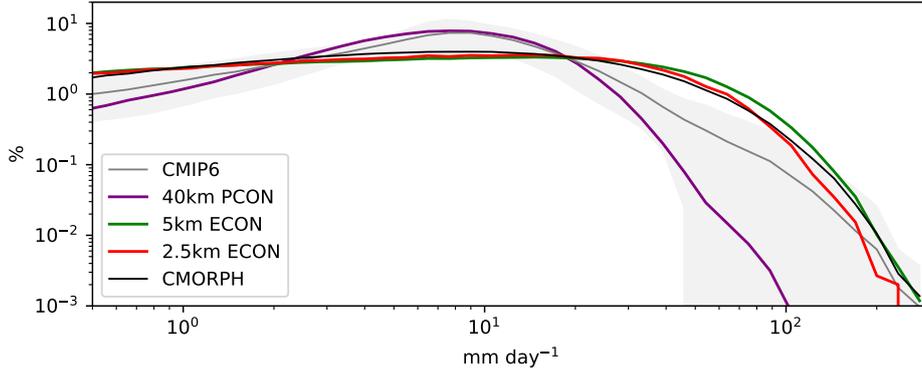


Figure 3. Distribution (%) of daily precipitation intensity greater than 0 mm over the Amazon basin for observations (black line) and simulations (colored lines). Values are binned in a logarithmic scale. The gray shading represent the standard deviation of 14-models of the CMIP6 ensemble.

283 inter-model variability in the representation of intense precipitation is large across the
 284 CMIP models, showing a larger frequency of the multi-model ensemble mean than the
 285 P-CON ensemble but still well below what is observed. The persistence of this too fre-
 286 quent and too gentle bias (Stephens et al., 2010; Fiedler et al., 2020; Judt & Rios-Berrios,
 287 2021) in all simulations employing parameterized convection suggests that it is not eas-
 288 ily addressed in the framework of existing convective parameterizations. The consider-
 289 ably better agreement between observations and simulations that represent convection
 290 explicitly, suggests that linking precipitation development to convective motion fields places
 291 physical and meaningful constraints on the intensity distribution in ways that param-
 292 eterizations of convection are unable to mimic.

293 3.3 Diurnal cycle

294 The diurnal cycle of precipitation over the Amazon is not spatially homogeneous.
 295 To illustrate this feature, we compute the hourly mean for each grid point and then se-
 296 lect the time when precipitation is maximum (Fig. 5). This method allows us to con-
 297 sider semidiurnal variations and avoid ambiguities that arise when using the first har-
 298 monic approach (Yang et al., 2008).

299 A large part of the Amazon basin depicts a precipitation maxima in the afternoon
 300 from 15 to 18 Local Time (LT) as a result from daytime heating. The afternoon peak

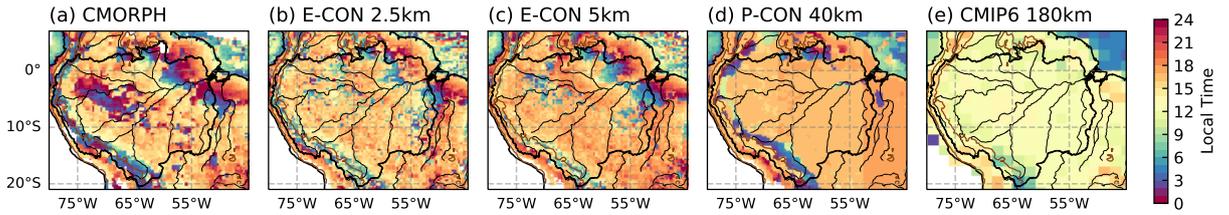


Figure 4. Local time (hour) of maximum precipitation in (a) CMORPH observations and simulations with explicit (E-CON) convection at (b) 2.5 km, (c) 5 km, parameterized convection (P-CON) at (d) 40km and the (e) CMIP6 multi-model ensemble mean. Observations and model outputs are regridded to 40km except for CMIP6 models which were interpolated to a common grid of about 180km and only serves as a reference. In all cases, the hourly mean was calculated and smoothed using a second order Fourier transform per grid point. The Amazon basin is defined as black contours as well as the rivers, and the topography at 1000 m is shown in brown contours.

301 is reasonably well represented by E-CON and P-CON, although in the case of the lat-
 302 ter elements of the parameterization were specifically designed to capture this effect (Bechtold
 303 et al., 2008). Nonetheless, it shows that such delays can be represented in the framework
 304 of convective parameterization, and thus constitutes an important improvement, but one
 305 that apparently has yet to find its way to the CMIP6 multi-model ensemble (Fig.4, e),
 306 as these models still tend to precipitate too early (Fiedler et al., 2020; Tang et al., 2021).
 307 Perhaps due to the way in which it was implemented, the P-CON simulations displays
 308 a rather homogeneous spatial distribution of the time of maximum precipitation. The
 309 E-CON simulations, on the contrary, are able to reproduce observed spatial heterogeneities
 310 in the diurnal cycle naturally. The time of diurnal precipitation maxima varies between
 311 15 to 18 LT, albeit the 5 km E-CON ensemble displays predominantly a peak time closer
 312 to 18LT in contrast to the 2.5 km ensemble.

313 The spatial heterogeneity of the diurnal cycle in the E-CON ensemble shows a struc-
 314 ture that is also evident in the observations. Notable in this respect is the consecutive
 315 peaking times from the northeast coast moving inland towards the Amazon. Near the
 316 coast, precipitation maximizes close to midday (12-14LT), a feature that may be related
 317 to relatively shallow and unorganized convection (e.g., Houze Jr et al., 2015). Precip-
 318 itation maximizing later in the day, increasingly so as one moves inland, is in agreement

319 with what would be expected from transition to deep convection that propagates towards
320 the Amazon (Greco et al., 1990; Burleyson et al., 2016). The representation of such pro-
321 gressive peaking times and corresponding increasing cloud depth (not shown) suggest
322 that the E-CON ensembles are able to reproduce a realistic transition of convection.

323 Notwithstanding the general tendency of precipitation to maximize during the day,
324 there are places where precipitation peaks overnight (Garreaud & Wallace, 1997; Rick-
325 enbach, 2004; Janowiak et al., 2005; Tanaka et al., 2014). Two regions stand out in CMORPH
326 data displaying a horse-shoe pattern (Fig. 4, a). This structure is captured by the E-
327 CON ensembles (Fig.4, b and c) but is not observed in P-CON or CMIP6. For instance,
328 the northeast extreme of the Amazon basin exhibits a coast-parallel band of consecu-
329 tive peaking times from 21LT to 6LT (Fig.4, a, b and c). This nocturnal precipitation
330 band has been associated with squall lines, which can originate at the coast and move
331 inland (e.g., Garstang et al., 1994). Other places displaying nocturnal precipitation peaks
332 are not as pronounced in the E-CON ensembles as in observations, but still can be dis-
333 tinguished inland between 6°W - 75°W , 5°S - 0°W and over the southeast Amazon (50°W -
334 55°W , 15°S - 10°S). Many of the nocturnal precipitation peaks also co-locates with the Ama-
335 zon river and its tributaries, suggesting a sensitivity to the representation of thermally-
336 driven local circulations (e.g., Fitzjarrald et al., 2008; Tanaka et al., 2014; Wu et al., 2021).
337 Over the eastern flank of the Andes, particularly south of 10°S , a nocturnal peak in pre-
338 cipitation is apparently captured by the P-CON ensemble. Closer inspection shows an
339 eastward misplacement of these systems in P-CON, whereas they are better captured
340 by the E-CON ensembles, increasingly so as the grid is refined.

341 In terms of the amplitude of the precipitation diurnal cycle, Figure 5 shows that
342 both E-CON ensembles particularly overestimate precipitation associated with deep con-
343 vection (at about 15-17LT). However, in contrast to the results of Inoue et al. (2021),
344 the secondary peak in the early morning is slightly underestimated and rather delayed
345 by 3 hours in both E-CON ensembles. There is not considerable differences between the
346 2.5 km and 5 km ensembles regarding the amplitude, but only in the phase as shown in
347 Fig. 4.

348 The representation of the diurnal cycle in the Amazon basin thus proves to be an-
349 other major area susceptible to the more physical constraints associated with an explicit
350 representation of convection, a finding that is in agreement with a recent study by Tai

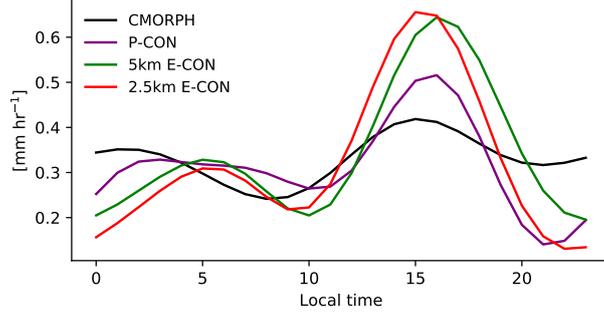


Figure 5. Diurnal precipitation averaged over the Amazon basin.

351 et al. (2021). Moreover, differences between the 2.5 km and 5 km are more prominent in
 352 the time of maximum precipitation, which suggests an improvement with a reduced grid
 353 spacing for a daytime precipitation maxima and nocturnal precipitation maxima along
 354 the Andes.

355 **4 Role of organized convective systems**

356 In section 3 we compared some precipitation characteristics between observations
 357 and small ensembles of simulations, differing in their treatment of convection and in their
 358 spatial resolution. An explicit representation of convective precipitation is shown to im-
 359 prove the representation of Amazon precipitation, most notably in terms of the distri-
 360 bution of precipitation intensity and the spatial heterogeneity of the diurnal cycle. These
 361 precipitation characteristics can be related to organized convective systems, which de-
 362 velop during the day and can last overnight generating very intense rainfall episodes (e.g.,
 363 Garreaud & Wallace, 1997; Rickenbach, 2004; Pereira Filho et al., 2015; Rehbein et al.,
 364 2018).

365 In this section we analyze whether improvements in the representation of the pre-
 366 cipitation intensity and diurnal cycle by the E-CON ensembles are related to the rep-
 367 resentation of organized convective systems in the Amazon. Since simulations with pa-
 368 rameterized convection fail in reproducing such precipitation features (i.e. high inten-
 369 sity rain rates and nocturnal precipitation peaks), we exclude them from further anal-
 370 ysis.

371 In the following subsections we examine precipitation characteristics of precipita-
 372 tion objects and compare them with the non-organized precipitation. To define a pre-
 373 cipitation object, or what we call an organized convective systems (OCS) we use an object-
 374 based approach. First, precipitation is associated with grid cells whose hourly rain rate
 375 is equal to or greater than 2 mm h^{-1} . Precipitation objects are then identified as con-
 376 tiguous grid cells (8-way connection) with a minimum size of $10\,000 \text{ km}^2$ (equivalent to
 377 six grid cells on the coarsened analysis grid) at each hour. Given that we do not track
 378 the OCS, this method preferentially samples mature systems. This is why we chose a
 379 size threshold similar to the mean size found in past studies (Rehbein et al., 2018; Anselmo
 380 et al., 2021), which are about $14\,000 \text{ km}^2$ (based on brightness temperature). Even so,
 381 we test our findings by redoing the analysis using different thresholds and this did not
 382 change our findings.

383 4.1 Frequency of intensity and size

384 Figure 6 (a) shows the distribution of precipitation intensity of OCS only (solid lines)
 385 and non-organized precipitation (dashed lines). By comparing Fig. 6 (a) with Fig. 3 one
 386 can notice a better agreement between the E-CON ensembles and CMORPH data when
 387 only considering the OCS. In particular, the 5 km ensemble fits well the observations be-
 388 tween 10 mm d^{-1} to 200 mm d^{-1} .

389 Precipitation associated with OCS explains the high-intensity rates ($>100 \text{ mm d}^{-1}$)
 390 in observations. The distribution of non-organized precipitation in CMORPH resembles
 391 the P-CON distribution in Fig. 3. In contrast, non-organized precipitation in the E-CON
 392 ensembles still shows larger frequencies of intense rain (around 200 mm d^{-1}). This shows
 393 a tendency of the E-CON simulations to produce more intense isolated events, which is
 394 an expected deficiency at kilometer-scale resolutions given that convection is not fully
 395 resolved (Prein et al., 2015; Arnold et al., 2020).

396 The relative contribution of OCS to the total rainfall can be associated with the
 397 distributions of precipitation intensity. In observations, most of the intense precipita-
 398 tion ($>50 \text{ mm d}^{-1}$) is associated with OCS (e.g., Feng et al., 2021). The contribution of
 399 OCS in the E-CON ensembles is not as large as observed (30% in the simulations as com-
 400 pared to about 50% in the observations, not shown), a bias that may arise because high

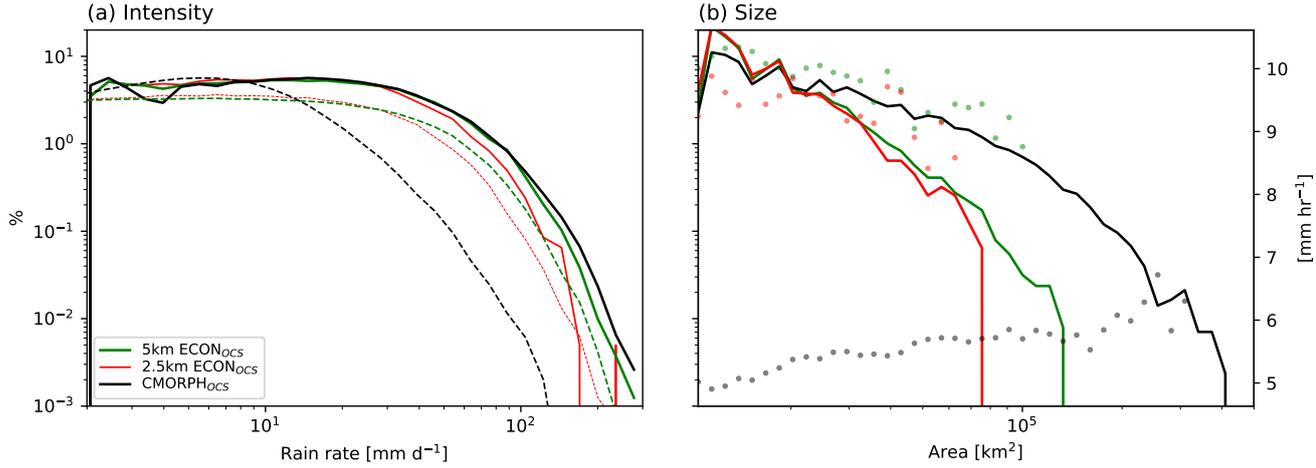


Figure 6. (a) Distribution (%) of daily precipitation intensity of organized convective systems (OCS, solid lines) and non-organized precipitation (dashed lines) in the Amazon basin. (b) Size distribution of organized convective systems (solid lines) and mean precipitation per area bin (scatter points, right axis). Observations are displayed in black and the E-CON ensembles, in green (5 km) and red (2.5 km) colors. Values of intensity and size are binned in a logarithmic scale.

401 intensity rates are present in the non-organized precipitation events to a greater degree
 402 than in the observations.

403 Another feature related to the precipitation intensity in OCS is their size (Fig. 6,
 404 b). As found in some previous studies (e.g., Crook et al., 2019; Arnold et al., 2020), the
 405 storm-resolving simulations generally produce smaller precipitation clusters than those
 406 identified in observations. The median size for 5 km and 2.5 km E-CON ensembles are
 407 $14\,411\text{ km}^2$ and $14\,371\text{ km}^2$, respectively; whereas for CMORPH it is $19\,224\text{ km}^2$. Like-
 408 wise, the median intensity per bin size is about twice in E-CON than CMORPH (col-
 409 ored dots in Fig. 6, b). The size distribution of OCS shows that E-CON overestimates
 410 the frequency of systems smaller than $<20\,000\text{ km}^2$ and misses those larger than $150\,000\text{ km}^2$.

411 The large discrepancies of OCS intensity and size between E-CON and observa-
 412 tions do not change considerably between 2.5 km and 5 km ensembles, meaning that these
 413 biases might be associated with unresolved processes (i.e sub-hectometer scales) such as
 414 cloud microphysics. For instance, Feng et al. (2018) found that a better representation
 415 of stratiform rain results in a better representation of precipitation area in mesoscale con-

416 vective systems at storm-resolving resolutions. This suggests that microphysical processes
 417 might be important for properly representing some macrophysical properties of OCS in
 418 the Amazon (e.g. size).

419 **4.2 Diurnal cycle**

420 Considering precipitation only from OCS improves the similarity of the spatial struc-
 421 ture in the phase of the diurnal cycle between E-CON and observations (Fig. 7, a, b and
 422 c). Especially in the western Amazon, precipitation peaks occurring during night and
 423 early morning are as apparent in the 5 km E-CON ensemble as in CMORPH. This fea-
 424 ture is noisier in the 2.5 km ensemble probably due to the smaller sample size than the
 425 5 km ensemble.

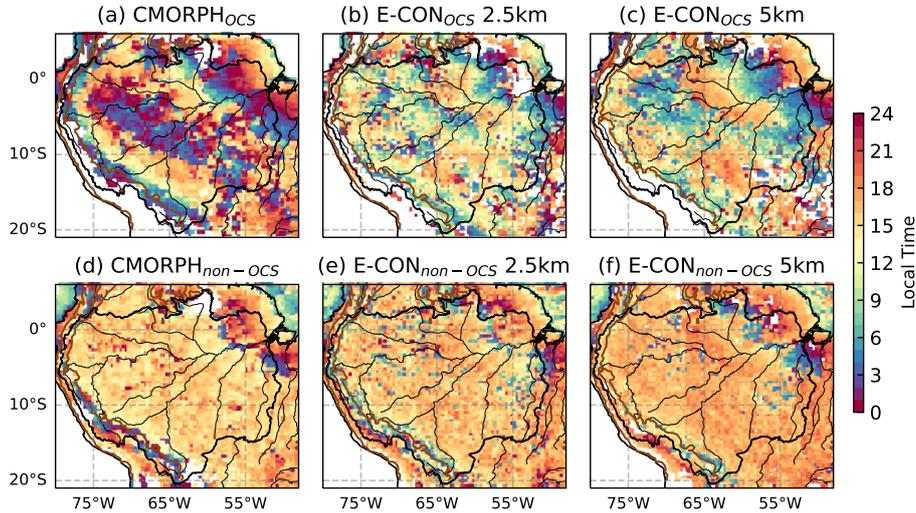


Figure 7. Local time (hour) of maximum precipitation (a, b, c) considering only organized convective systems (OCS) and (d, e, f) only non-organized precipitation ("*non-OCS*") for (a, d) CMORPH, (b, e) 5 km E-CON and (c, f) 2.5 km E-CON simulations. For the purpose of this figure, the identification of OCS considered regions outside the Amazon. The Amazon basin is defined as black contours as well as the rivers, and the topography at 1000m is shown in brown contours.

426 The OCS explain most of the spatial heterogeneity in the diurnal cycle of precipi-
 427 tation in observations (compare Fig. 7, a, d and Fig. 4, a). This feature is less in ev-
 428 idence in E-CON over the central Amazon, although the reduced frequency of OCS in

429 the E-CON ensembles (about one third of CMORPH, not shown) may explain the dif-
 430 ference with observations. While there is a clear nocturnal maximum in the simulated
 431 OCS precipitation, it is delayed by a few hours as compared to observations. CMORPH
 432 displays a nocturnal peak preferably between midnight and 3LT, whereas peaks between
 433 3LT to 6LT are more apparent in the 5 km E-CON ensemble. In contrast, diurnal peaks
 434 (12LT to 18LT) are more similar between CMORPH and E-CON, especially at 2.5 km.
 435 Other features associated with the diurnal cycle of OCS by E-CON are also consistent
 436 with the observations. For instance, the largest and less intense OCS are shown in the
 437 early morning, consistent with a decay stage of these systems (Houze Jr, 2004); whereas
 438 the most intense and smaller OCS take place in the late afternoon in agreement with their
 439 mature phase (not shown).

440 Non-organized precipitation features daytime precipitation maximum ranging mostly
 441 from 12 h to 18 h (Fig. 7 d, e, f), with predominantly peaking times at about 15LT in
 442 observations, at 16LT in the 2.5 km ensemble and at 18LT in the 5 km E-CON. Despite
 443 the overall diurnal peaks some regions display maximum precipitation overnight in both
 444 observations and E-CON ensembles. For instance, scattered nocturnal peaks in the cen-
 445 tral Amazon, probably associated with very intense rain rates from isolated convective
 446 cells (Fig.6, a), are placed near the Amazon river and its tributaries .

447 While diurnal precipitation peaks seem to improve with increased resolution (Sato
 448 et al., 2009), especially for non-organized precipitation, nocturnal precipitation peaks
 449 associated with OCS remain similar between 2.5 km and 5 km ensembles. This insensi-
 450 tivity to spatial resolution might indicate once more that other unresolved processes are
 451 important for representing the correct lifecycle of OCS in the Amazon.

452 **5 Environmental conditions related to OCS**

453 **5.1 Classification of OCS**

454 To better understand the structure of the simulated OCS and environmental fac-
 455 tors that influence them, we first apply the k-means clustering technique to objectively
 456 identify the main types of OCS in terms of their time of occurrence, size, intensity and
 457 location (defined as the center of gravity of each OCS) within the whole Amazon. We
 458 also use the Silhouette score (Rousseeuw, 1987), which finds the optimum number of clus-
 459 ters based on a measure of cluster cohesion and separation. The analysis is focused on

460 the 5 km E-CON ensemble, whereas CMORPH observations serve only for comparison
461 of the OCS classification.

462 Six OCS clusters are identified in both E-CON and CMORPH (Table 2, Fig. S1).
463 Among these, a clear distinction is associated with their time of occurrence rather than
464 their size or intensity. Given that OCS represent mature systems, we refer to those that
465 occur in the afternoon (12-18 hrs) as diurnal (D1, D2, D3), and to those that occur in
466 early morning (5-10 hrs) as nocturnal (N1, N2, N3) OCS. Each of them accounts for about
467 50 % of the total OCS in E-CON (49.4 % for diurnal and 50.6 % for nocturnal); whereas
468 in the observations, diurnal OCSs are more clearly favored (58.4 % versus 41.6 %).

Table 2. Summary of clusters features in the 5 km E-CON ensemble and CMORPH (in parentheses). The median values are presented for the local hour, intensity, area and location (latitude and longitude). The last column indicates the fraction that a given cluster represents from the total OCS.

Cluster	Local hour	Intensity (mm h ⁻¹)	Area (km ²)	Latitude	Longitude	Fraction (%)
D1	17 (18)	9.8 (4.9)	15 513.2 (21 742.6)	-2.8 (-9.0)	-64.1 (-60.6)	20.8 (22.9)
D2	12 (13)	9.0 (4.7)	15 561.69 (22 901.6)	-12.3 (-2.9)	-65.5 (-72.0)	16.3 (25.5)
D3	13 (13)	17.3 (8.8)	15 048.7 (25 949.4)	-5.7 (-5.2)	-65.9 (-67.1)	12.3 (10.0)
N1	6 (7)	9.0 (4.8)	16 671.1 (24 898.3)	-3.7 (-3.2)	-58.1 (-58.4)	22.6 (17.8)
N2	8 (5)	8.6 (4.8)	16 793.1 (23 447.9)	-3.4 (-11.5)	-72.6 (-65.5)	22.6 (17.5)
N3	9 (10)	9.4 (5.7)	47 832.2 (102 669.8)	-5.8 (-5.6)	-67.4 (-66.3)	5.4 (6.4)

469 Other common features between E-CON and CMORPH OCS are found in clus-
470 ters N1, N3 and D3. The N1-OCS distinguish from other nocturnal OCS because of their
471 center of gravity is placed in the northwest Amazon, which would correspond to the well-
472 known squall lines propagating from the coast (e.g., Garstang et al., 1994). N3 and D3
473 OCS do not show a preferred location of occurrence but they are characterized by their
474 large size and high intensity, respectively.

475 Contrasting the remaining OCS (N2, D1 and D2) between E-CON and CMORPH,
476 these mainly differ in their center of gravity and are more symmetrically distributed in
477 the simulations than observations (Fig. S1). For instance, D1-OCS and D2-OCS com-
478 prise the northern and southern Amazon in the E-CON ensemble, respectively; whereas

479 D2-OCS only cover the northwestern Amazon and D1-OCS, the rest of the basin in CMORPH.
 480 As opposed to N1-OCS, N2-OCS comprise the northwestern Amazon in E-CON; but they
 481 cover a large region in the southern Amazon in CMORPH. Notwithstanding these dif-
 482 ferences and the overall discrepancies regarding size and intensity of OCS as described
 483 in Section 4.1, we conclude that the E-CON ensemble makes a fair representation of the
 484 observed classification of OCS.

485 **5.2 Influence of the environment on OCS evolution**

486 We further explore the mean environmental conditions associated with OCS dur-
 487 ing their evolution by analyzing composites at different lead and lag times. To isolate
 488 diurnal and nocturnal events we consider OCS identified from 12LT (for diurnal OCS)
 489 and before 10LT (for nocturnal OCS).

490 Diurnal and nocturnal OCS show clear distinctions in their vertical structure (Fig.
 491 8), with some variations among clusters. For instance, diurnal OCS persist less than the
 492 nocturnal OCS at the place of detection. Both the cloud content and vertical velocity
 493 are considerably reduced at 3-hour lead in the diurnal clusters (Fig. 8, dotted lines), whereas
 494 nocturnal OCS show larger cloud content and vertical velocity from the freezing level
 495 (500 hPa) compared to the lower troposphere. This vertical structure suggests persistent
 496 and less intense precipitation in the nocturnal OCS consistent with stratiform features,
 497 an essential component of mature OCS (Houze Jr, 2004). In contrast, diurnal OCS dis-
 498 play enhanced convective activity (i.e vertical ascent) only at the time of OCS detection,
 499 which can be related to a shorter life span or faster propagation than the nocturnal OCS.

500 The diurnal OCS are associated with a strong (2 K) depression of the surface po-
 501 tential temperature relative to the environment (Fig. 9). This local signal is thought to
 502 be related to cold pools as shown in Figure 10. The time of detection of cold pools dis-
 503 plays successive times of occurrence from 12LT to 17LT in agreement with the OCS prop-
 504 agation, especially in the northeastern Amazon. Figure 9 shows westward-propagating
 505 anomalies of potential temperature which are stronger 3 hours before than after the de-
 506 tection of OCS, in agreement with the occurrence of cold pools mainly during the early
 507 afternoon. The westward propagation is consistent with the background zonal flow (Fig.
 508 8), which displays easterlies through a deep layer (from 950 hPa to 400 hPa). This prop-
 509 agation is more evident in D1-OCS (northern Amazon) and D3-OCS (most intense OCS),

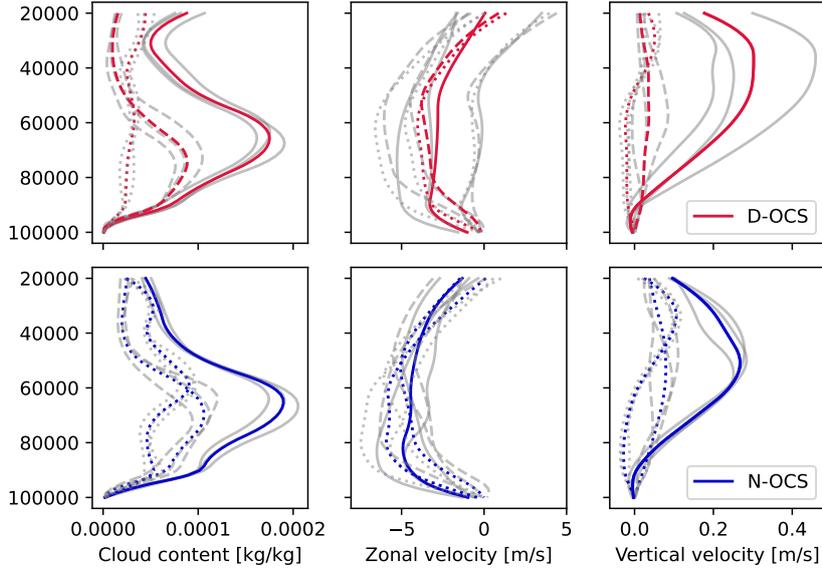


Figure 8. Vertical profile of composite OCS. The variables shown are from left to right: cloud content (water and ice), zonal velocity and vertical velocity. Solid contours represent the vertical profiles at the moment of object detection (time 0), dashed lines represent 3 hours before the detection and dotted lines, 3 hours after time 0. Diurnal (D-OCS) and nocturnal (N-OCS) OCS are located in the upper and lower row, respectively. Grey contours represent the original clusters (D1, D2, D3, N1, N2, N3). The vertical profiles are smoothed using a second order polynomial interpolation.

510 whereas D2-OCS (southern Amazon) show rather a stationary pattern, probably due to
 511 their far distance from the trade winds (not shown).

512 The nocturnal OCS are associated with different large scale conditions as compared
 513 to the diurnal OCS. The zonal wind velocity is considerably larger near 800 hPa (Fig.
 514 8) than the surface even 3 hours after the OCS detection, especially for N1-OCS (north-
 515 eastern Amazon) and N3-OCS (largest OCS). The strong easterlies in the lower tropo-
 516 sphere can be indicative of the nocturnal low-level jet (Anselmo et al., 2020), which would
 517 act against the stable nocturnal boundary layer to sustain convection overnight (e.g., Houze Jr,
 518 2004). Anselmo et al. (2020) found enhanced occurrence of cloud clusters associated with
 519 such nocturnal low-level jet, especially during the early morning (2LT to 8LT) which is
 520 in agreement with our results. Moreover, the potential temperature perturbations show
 521 larger anomalies above the surface (850 hPa) during the OCS occurrence (Fig. 9). A spe-

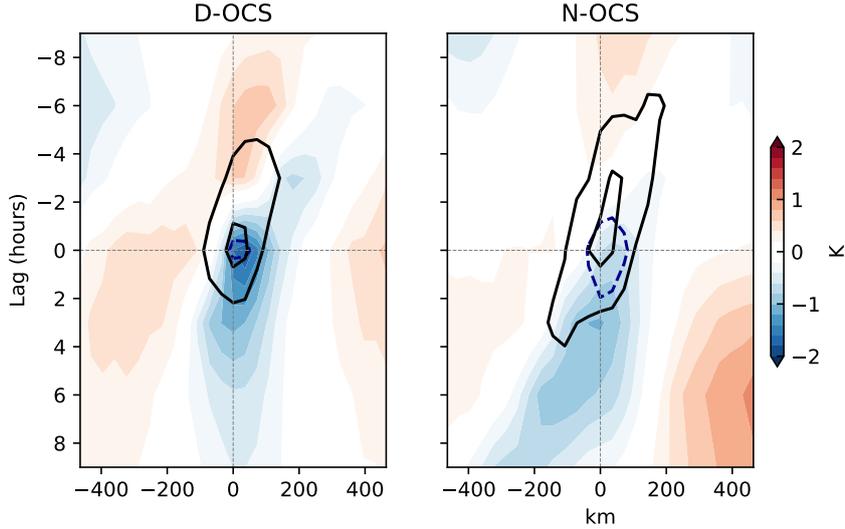


Figure 9. Time-longitude composites of potential temperature perturbations at the surface (1000hPa) related to diurnal (left) and nocturnal (right) OCS. Negative anomalies at 850hPa are shown as dashed-blue contours (-0.3 K). The anomalies are computed with respect to the zonal mean. Precipitation is displayed as black solid contours (0.2 and 0.5 mm h^{-1}). Time zero indicates the hour when the objects are detected and longitude zero is the location of the center of mass of the precipitating objects.

522 cial case is noted in N3-OCS (not shown), which display broader anomalies of potential
 523 temperature that last 3 hours after their detection. These elevated anomalies might be
 524 related to cooling by evaporation of precipitation particles and indicative of their decay
 525 stage.

526 The environmental controls of diurnal and nocturnal OCS as represented by ex-
 527 plicitly resolved convection, provide insights of which processes might be important and
 528 could be improved. For instance, it was mentioned that the frequency of OCS is consid-
 529 erably less in the E-CON ensembles than observations. More precisely, it appears that
 530 the diurnal OCS are those rather underestimated. The results show that surface processes
 531 matter mainly for the diurnal OCS, which suggest that these processes in relation to deep
 532 precipitating convection might need to be better represented at storm-resolving scales.

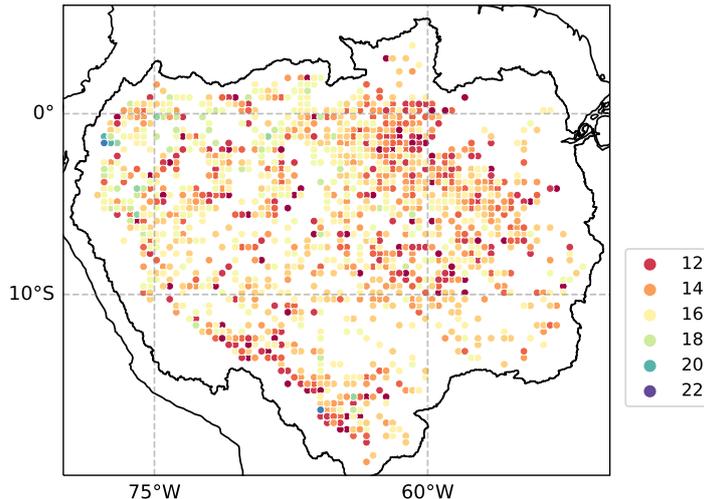


Figure 10. Local hour of cold pool detection during the time of occurrence of OCS. Cold pools are identified considering a potential temperature perturbation larger than -2K and precipitation greater than 1 mm h^{-1} .

533 6 Summary and conclusion

534 This study investigates the ability of storm-resolving simulations to represent precipitating systems over the Amazon river basin. We perform ensemble simulations with the ICON-NWP atmospheric model at a coarse grid spacing (40 km) wherein convection is parameterized (P-CON) and storm-resolving simulations that enable the explicit representation of convection (E-CON) at 2.5 km and 5 km grid spacing. The simulations are compared to each other, conventional coarse resolution model output taken from CMIP, and to observations as represented by the CMPORPH dataset.

541 The mean precipitation in the Amazon basin and its spatial distribution is fairly represented by both E-CON and P-CON ensembles. However, the large frequency of light rain can explain a close daily mean to observations in the P-CON ensemble. Moreover, P-CON misses precipitation in the northeast coast which is known to be important for the generation of propagating systems towards the Amazon (e.g., Greco et al., 1990; Burleyson et al., 2016; Rehbein et al., 2018).

547 Ensembles with grid spacings that allow for explicit convection better represent the distribution of precipitation intensity and the spatial variability of the diurnal cycle, as compared to simulations with parameterized convection. Light-to-moderate precipita-

550 tion 2 mm d^{-1} to 20 mm d^{-1} and higher intensity rain rates are correctly captured by E-
551 CON; whereas P-CON persists on long-standing biases (e.g., Stephens et al., 2010) as
552 the CMIP models. The spatial heterogeneity (pattern) of the diurnal cycle can also be
553 detected in the E-CON ensemble, similar to what is found in observations. The P-CON
554 ensemble, which is based on one of the best tested and most advanced parameterization
555 schemes, while able to reproduce the afternoon peak of maximum precipitation over most
556 of the Amazon in contrast to the CMIP models, its spatial distribution is rather homo-
557 geneous and misses the nocturnal precipitation over the central and northeast Amazon.

558 The E-CON ensemble shows evidence of organized convective systems that are ab-
559 sent in the P-CON ensemble. These OCS are shown to be closely associated with the
560 better representation of Amazon precipitation, as they explain the frequency of high in-
561 tense rain rates and the heterogeneity of the precipitation diurnal cycle in observations.
562 The similarity between E-CON and observations improves in both the distribution of pre-
563 cipitation intensity and diurnal cycle when only considering precipitation from OCS. How-
564 ever, the simulated OCS simulated by the E-CON ensemble are still less frequent, smaller
565 and more intense than observed.

566 The simulated and observed OCS cluster into nocturnal and diurnal systems. The
567 environment of the nocturnal versus diurnal systems differs systematically. Nocturnal
568 clusters are associated with stronger easterlies in the lower troposphere, peaking at about
569 850 hPa and forming part of the Amazonian low-level jet (Anselmo et al., 2020). In ad-
570 dition, an elevated cooler atmosphere propagates with the OCS during the early morn-
571 ing. Not surprisingly, the diurnal OCS show a stronger signature at the surface than the
572 nocturnal OCS. The E-CON simulations suggest that cold pools contribute to the prop-
573 agation of OCS in the northern Amazon and those that are very intense (D3-OCS). A
574 composite analysis over diurnal clusters shows a strong temperature perturbation at the
575 surface that propagates during the early afternoon. Given that the simulations produced
576 about 20% less of diurnal OCS than observations, such systems may be sensitive to the
577 representation of surface processes in ways that the E-CON simulations insufficiently cap-
578 ture.

579 Our simulations show a clear improvement in many aspects of precipitation over
580 the Amazon river basin when the precipitating systems are simulated explicitly. By sim-
581 ulating the geometry and transient dynamics of precipitating convection systems, a bet-

582 ter representation of organized convective systems emerge, and these prove essential for
583 capturing many features of the observed precipitation over the Amazon. Nonetheless,
584 our simulations also show room for improvement. For instance in representing the rel-
585 ative prominence of organized systems during the day, which may be sensitive to land-
586 surface processes, and in the timing of the nocturnal peak of precipitation, which has
587 previously been shown to be sensitive to cloud microphysical processes (e.g., Feng et al.,
588 2018). Simulations with a twofold finer grid do not lead to dramatic improvements, in-
589 dicated that to the extent deficiencies are related to a poor representation of small scale
590 circulations, capturing these effects explicitly would require much (hecto to deca meter)
591 finer resolution.

592 **7 Open Research**

593 HadISST data (Rayner et al., 2003) is available at <https://www.metoffice.gov.uk/hadobs/hadisst/data/download>
594 CMORPH precipitation dataset (Xie et al., 2017) were obtained from [https://www.ncei.noaa.gov/data/cmorph-](https://www.ncei.noaa.gov/data/cmorph-high-resolution-global-precipitation-estimates/access/30min/8km)
595 [high-resolution-global-precipitation-estimates/access/30min/8km](https://www.ncei.noaa.gov/data/cmorph-high-resolution-global-precipitation-estimates/access/30min/8km). Boundaries of the Ama-
596 zon are available at Lehner et al. (2006) and were obtained from <http://hydrosheds.cr.usgs.gov>.
597 CMIP output of this study were replicated and made available for this study by the Ger-
598 man Climate Computing Centre (Deutschen Klimarechenzentrum, DKRZ) and pre-processed
599 at Fiedler et al. (2020). Primary data and scripts used in the analysis that may be use-
600 ful in reproducing the author’s work are archived by the Max Planck Institute for Me-
601 teorology and can be obtained via the institutional repository <https://pure.mpg.de>

602 **Acknowledgments**

603 This study was supported by the Max Planck Society for the Advancement of Science
604 and . The authors thank Jaemyeong Seo for providing scripts for the cold pool detec-
605 tion and Cathy Hohenegger for her useful and constructive comments on the paper.

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Supporting Information for

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Assessing precipitation over the Amazon basin as simulated by a storm-

5

resolving model

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10 **Contents of this file**

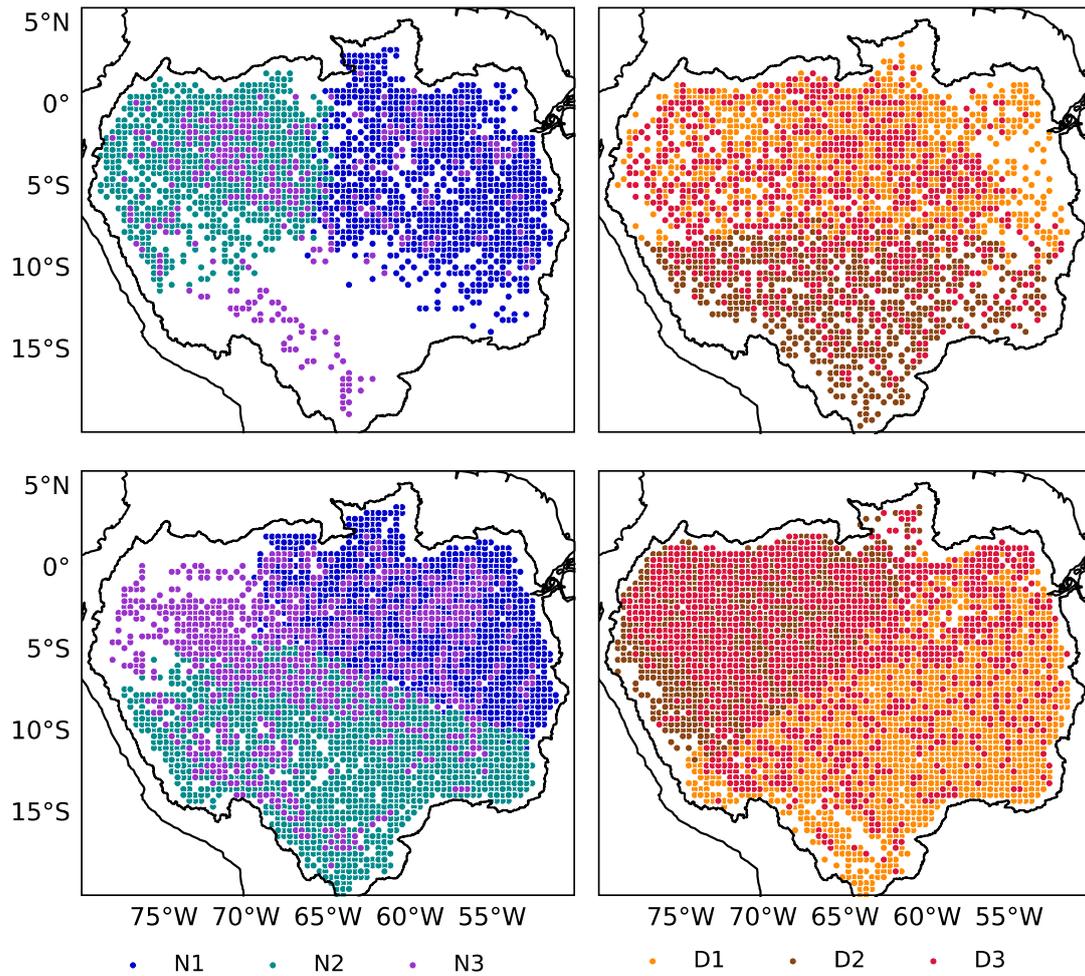
11 Figure S1

12

13 **Introduction**

14 This supporting information provides an additional figure.

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19 **Figure S1.** Location of diurnal (D1, D2, D3) and nocturnal (N1,N2,N3) organized

20 convective systems (OCS) in 5km E-CON ensemble (upper row) and CMORPH

21 observations (lower row)