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The representation of dry-season low-level clouds over Western Equatorial Africa
in reanalyses and historical CMIP6 simulations

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Availability of data and material: all the data used in this work are publicly available. ISD cloud data are accessible from www.ncdc.noaa.gov/isd/data-access, and EECRA cloud data from NCAR at climateguide.ucar.edu/climate-data. The CALIOP satellite data come from the GCM-Oriented CALIPSO Cloud Product (GOCCP) at climserv.ipsl.polytechnique.fr/cfmip-obs/Calipso_goccp.html. ERA5 reanalyses are available from <https://cds.climate.copernicus.eu> and MERRA-2 from [gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data access](http://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data_access). CMIP6 data can be downloaded from esgf-node.llnl.gov/search/cmip6.

Authors' contributions: Not applicable

1 Abstract

2 Western Equatorial Africa (WEA) has a record low sunshine duration during the June–September dry
3 season due to the persistence of low clouds. This study examines the ability of two reanalysis products
4 (ERA5 and MERRA-2) and 8 CMIP6 models (both coupled and atmosphere-only historical simulations)
5 to reproduce the climatology of these low clouds, by comparing it with ground observations and a
6 satellite product. All datasets show a reasonable representation of the regional distribution of low
7 clouds over the Tropical Atlantic and the neighbouring African continent. However, CMIP6 models tend
8 to underestimate the low cloud fraction, especially over WEA in the coupled simulations. This
9 underestimation is partly due to an insufficient seasonal sea-surface temperature (SST) cooling over
10 the Eastern Equatorial Atlantic from April to July in most models, which contributes to reducing the
11 lower-tropospheric stability (LTS). ERA5 data, whose dry season WEA low-cloud fraction is close to
12 observations, indicate that LTS strongly controls the interannual variability of WEA low clouds.
13 Interestingly, the ability to reproduce the mean low cloud fraction does not necessarily scale with the
14 SST biases of the CMIP6 models. The strong dependence of low clouds on interannual SST variations
15 in ERA5 is captured by less than half of the CMIP6 models. Additional key drivers of interannual
16 variations identified in this study, such as Bight of Bonny surface winds and mid-tropospheric
17 temperatures, actually show up inconsistently in CMIP6. Further analyses are needed to disentangle
18 the roles played by SST and independent atmospheric forcings on WEA low cloud formation.

19

20 Keywords

21 cloudiness - sea-surface-temperature - CMIP6 - Equatorial Africa - Equatorial Atlantic Ocean

22

23 1. Introduction

24 Much of climate research focusing on tropical land areas is dedicated to precipitation variability and
25 its driving mechanisms. Dry seasons generally attract less attention, since they are considered as
26 periods of relatively steady, stable and cloudless weather. In Western Equatorial Africa (WEA),
27 especially in Gabon and southern Congo-Brazzaville, the austral winter season from June to September
28 is rainless but is unexpectedly also the time of the year showing the least sunshine and the highest
29 cloud amounts (Bush et al. 2019; Philippon et al. 2021). Over the Mayombe range in Congo-Brazzaville,
30 mean dry season sunshine duration is under one hour per day (Bouka-Biona et al., 1993). The extensive
31 low cloud cover found during this season is associated with relatively low daytime temperatures, which

32 reduces evapotranspiration and is likely to play a key role in the survival of an evergreen forest in much
33 of the region, despite the long dry season of up to 4 months (Clairac et al. 1989; Couralet et al. 2010 ;
34 Philippon et al. 2019; Réjou-Méchain et al. 2021).

35 Dry season low-level clouds in WEA tend to be highly persistent, with occurrences above 80% in Gabon
36 based on synoptic observations (Dommo et al., 2018). They usually take the form of a stratocumulus
37 cloud deck with maximum cloud fraction near 850-900 hPa (Dommo et al. 2018). This cloud deck occurs
38 within the southwesterly monsoon flow, which along the coast is about 1000 to 2000 m deep during
39 this season (Lacaux et al. 1992). The monsoon flow is topped by a temperature inversion (Berruex,
40 1958; Tschirhart, 1959; Trewartha, 1981). While stratocumulus cloud decks are recurrent features over
41 the eastern flanks of subtropical anticyclones covering oceanic areas (Klein and Hartman, 1993; Wood,
42 2012; Eastman and Warren, 2014), there are more uncommon over equatorial land areas. They are
43 found in Western Africa along the Gulf of Guinea coastal zone (Fink et al. 2011; Knippertz et al. 2011 ;
44 Schrage and Fink, 2012; Schuster et al., 2013 ; Dione et al., 2019; Hannak et al., 2017; Danso et al.
45 2020), also from July to September, but their frequency is not as high as in Western Equatorial Africa.
46 A stratocumulus cloud cover is also a recurrent feature in austral winter at Nairobi (Kenya), on the
47 east-facing (windward) slopes of the East African Highlands, suggesting a key role of orography
48 (Camberlin, 2018).

49 Although the WEA low clouds are not strictly a coastal phenomenon, since they extend to about 300-
50 400 km inland (Dommo et al., 2018; Phillipon et al. 2019), their location east of the Equatorial Atlantic
51 Ocean at a time when the seasonal coastal and equatorial upwelling reaches its maximum intensity
52 suggests that sea surface temperature (SST), combined with the onshore low level flow, is an important
53 control. However, the mechanisms of the low cloud formation over this region and its representation
54 in models are not well known. Further south over the Southeast Atlantic Ocean, there is still some
55 uncertainty on the exact role played by the cool marine surface, given the complex feedbacks between
56 clouds and surface temperature (Philander et al. 1996; Trzaska et al. 2007; Bellomo et al. 2015). Adebisi
57 and Zuidema (2018) found that both meteorological factors (including atmospheric stability and large-
58 scale subsidence) and aerosol forcing (biomass-burning aerosols from Southern Africa) contribute to
59 the development of the persistent low-level cloud deck over this area, while Koseki and Imbol Koungue
60 (2021) showed that March-April low-level clouds were enhanced in years of cold SST anomalies along
61 the Angolan coast (called 'Benguela Niña' events, Shannon et al. 1986). Even further south, for the
62 coastal Namib Desert Andersen et al. (2020) showed that fog and low-cloud occurrence is controlled
63 by variations in cloud-top longwave cooling and the strength of the onshore flow, both modulated by
64 synoptic-scale disturbances.

65 Uncertainty also revolves around the capability of global circulation models (GCMs) and even
66 reanalysis products to reproduce this low cloud cover. Low clouds are known to be difficult features to
67 model (Dufresne and Bony, 2008; Lauer and Hamilton, 2013; Zelinka et al., 2017; Myers et al. 2021).
68 Over the tropical and subtropical zones, simulated low clouds tend to be too few and too bright, i.e.
69 have an overestimated optical thickness, likely due to a vertical overlap of cloud layers (Nam et al.
70 2012; Cesana and Walliser, 2016). Within the GCMs participating in the CMIP5 experiment, there is
71 also a large inter-model diversity in the relationship between marine low clouds and SST (Cesana et al.
72 2019). The poor simulation of marine low clouds should be considered along with the warm SST bias
73 often found over these regions. Hu et al. (2008) suggested that the underestimation of low clouds was
74 by itself a potential cause of the warm SST bias over the southeastern Atlantic Ocean. Xu et al. (2014),
75 however, found that the overestimation of shortwave radiation associated with the insufficient marine
76 low clouds in CMIP5 models was not the leading cause of the warm bias, and hypothesized a role of
77 eddy-induced ocean heat transport. For southern West Africa, Hill et al. (2016) found a strong
78 underestimation of June-July low cloud cover in both ERA-Interim reanalysis data and CMIP5
79 atmospheric models forced by prescribed SSTs. Hannak et al. (2017), for the same region, analysed a
80 larger number of CMIP5 models and showed that their simulation of low-level clouds was only
81 marginally improved from that of previous generation models (CMIP3). The underestimation of low-
82 cloud cover appears to be related to the subgrid cloud schemes, and to too low near-surface relative
83 humidity at daytime, associated with abundant solar radiation and too high daytime maximum
84 temperatures. No study ever examined the skill of climate models in the simulation of low cloud cover
85 over WEA, despite its temporal persistence during the dry season and major feedbacks on the local
86 climate.

87 This study will make use of newly available CMIP6 simulations, with the aim to address the following
88 questions: (i) are global climate models and two recent reanalysis products (i.e. ERA5 and MERRA2)
89 capable of realistically representing the low clouds present in WEA? (ii) are the low clouds of this region
90 a mere extension of the large-scale low cloud deck found over the Southeast Atlantic Ocean? (iii) do
91 CMIP6 GCMs underestimate low clouds as in the previous model generations, and is there any
92 difference between atmospheric and coupled simulations? (iv) how does the low cloud cover relate to
93 oceanic and atmospheric forcings, in models and reanalyses? (v) do these relationships help to
94 understand the models' systematic biases in their reproduction of low clouds? To answer these
95 questions, low cloud cover will be compared between CMIP6 historical simulations (both coupled and
96 atmospheric only), both reanalysis products, Cloud-Aerosol Lidar with Orthogonal Polarization
97 (CALIOP) satellite data and in situ synoptic observations for WEA. The focus will be on the austral
98 winter dry period (June–September) during which most of the low clouds develop over the region, but

99 insights will also be given into the annual cycle. Besides the examination of mean fields, interannual
100 variability will be considered, in particular the relationship between low cloud variability and SST over
101 the Equatorial Atlantic Ocean, which is suspected to play a significant role in (or least interact with)
102 low cloud occurrence.

103 Section 2 presents the different types of data and the methods used in the study. The climatology of
104 low level clouds is then examined (section 3.1), followed by an analysis of the interannual variations of
105 low clouds (section 3.2). Finally, their relationships with oceanic and atmospheric fields are studied in
106 section 3.3. Section 4 summarizes the results.

107

108 2. Data and methods

109 Four types of data sets are used (Table 1): satellite observations (CALIOP), surface observations (ISD
110 and EECRA), reanalyses (ERA5 and MERRA-2) and simulations from climate models (CMIP6). All the
111 data (with some exceptions as noted below) are extracted over the period 1979–2014, which is
112 common to most data sets, at the monthly timescale. Low cloud definitions vary between these data
113 sets and are presented at the end of this section.

114

115 2.1 CALIOP

116

117 CALIOP (Cloud-Aerosol Lidar with Orthogonal Polarization) is the lidar device aboard the CALIPSO
118 satellite. CALIPSO (Cloud Aerosol Lidar and Infrared Pathfinder Satellite Observations) is a Franco-
119 American mission launched in 2006 with the objective of studying the radiative impacts of clouds and
120 aerosols on climate. CALIOP is a two-wavelength backscattering lidar (532 and 1064 nm) that provides
121 high-resolution vertical profiles of clouds and aerosols (Chepfer et al., 2008). The lidar detects all types
122 of clouds but low clouds can only be detected when they are not covered by optically thick higher
123 clouds. The data used in this study are not those obtained directly from the lidar but come from the
124 GCM-Oriented CALIPSO Cloud Product (GOCCP) (see below). The spatial resolution of the GOCCP low
125 cloud data is 2° in latitude and 2° in longitude, i.e. approximately a 200 km grid; hence they are used
126 to depict large-scale patterns only. The data are available from June 2006 and extracted up to
127 December 2019.

128

129 2.2 ISD

130

131 ISD (Integrated Surface Database) is a global database comprising hourly synoptic surface observations
132 made at meteorological stations (Smith et al., 2011). It is a database managed by the United States
133 NCEI (National Centers for Environment Information). It includes over 35,000 stations around the
134 world, with early data dating back to 1901, but many series beginning in the 1970s. Several parameters
135 are recorded in the database such as temperature, wind, cloudiness, precipitation. In Gabon and
136 Congo-Brazzaville, there are 30 stations with cloud data (sky cover, cloud ceiling, types of clouds – low,
137 middle and high) (figure 1a). Only the synoptic hours (i.e. GMT 0000, 0300, 0600 etc.) are retained.
138 Unfortunately, the records are rather incomplete. Only 15 stations have more than 25% of non-missing
139 3-hourly records over the period of study 1979–2014.

140

141 2.3 EECRA

142

143 EECRA (Extended Edited Cloud Report Archive) is a global cloud database (Hahn and Warren, 1999).
144 These data are surface observations from various sources which have been processed, edited after
145 quality control, from reports made by observers on ships or on the continent, day and night. Li et al.
146 (2015) found an excellent agreement at global scale between EECRA cloud data and various satellite
147 cloud products. Data from land stations cover the period 1971–2009, from which the sub-period
148 starting in 1979 has been extracted. Low cloud fraction is available at three-hourly resolution. There
149 are only 25 stations in the study area (figure 1b). The overall amount of missing data is close to that of
150 the ISD data set.

151 2.4 ERA5

152

153 ERA5 is the fifth generation of climate reanalysis data from ECMWF (European Centre for Medium-
154 Range Weather Forecasts). ERA5 replaces ERA-Interim, which ceased to be produced at the end of
155 August 2019 (C3S, 2017), and includes considerable improvements and higher horizontal, temporal
156 and vertical resolutions (Hersbach et al. 2020). The data are at a native horizontal resolution of 31 km,
157 made available on a 0.25-degree grid, and resolve the atmosphere at 137 levels from the surface to a
158 height of 80 km, on an hourly time scale. ERA5 uses the Tiedtke cloud scheme (Tiedtke, 1993) to
159 forecast a three-dimensional cloud fraction for each grid box. Monthly data are extracted over the
160 period 1979–2014. In addition to low cloud fraction, the following variables have been used: SST,
161 relative humidity, temperature, zonal and meridional winds at 1000, 925, 850, 700, 600 and 200 hPa.
162 For oceanic and atmospheric fields, the ERA5 reanalyses will serve as the reference.

163

164 2.5 MERRA2

165

166 MERRA (Modern-Era Retrospective analysis for Research and Applications) produced by NASA
167 (Rienecker et al., 2011) is a second set of reanalyses used in this study. The second generation of these
168 reanalyses (MERRA-2), starting from 1980, is used in this study. It is based on GEOS-5 for the
169 assimilation of the most recent sources of satellite data, in particular new microwave sounders and
170 hyperspectral infrared radiation instruments (Bosilovich et al., 2016). The resolution is $0.625^\circ \times 0.5^\circ$ or
171 approximately a 50km grid. Only low cloud data are extracted from MERRA-2 over the period 1980–
172 2014. The initial time step is 30 minutes, and data are integrated as monthly averages.

173

174 2.6 CMIP6

175

176 CMIP (Coupled Model Intercomparison Project) is an inter-comparison project of coupled ocean-
177 atmosphere climate models the objective of which is to better understand past, present and future
178 climate change. The project falls under the World Climate Research Program (WCRP) of the World
179 Meteorological Organization (Eyring et al., 2016) and is currently in its sixth phase (CMIP6). Data cover
180 the period 1850–2100 depending on the type of experiment, i.e. natural variability or response to
181 changes in radiative forcing.

182 The present work seeks to evaluate the models' performance to simulate the recent climate through
183 historical simulations, and projections are therefore not examined. Two types of experiments are
184 selected: coupled simulations and atmosphere-only simulations (AMIP: Atmospheric Model
185 Intercomparison Project). The historical coupled simulations are only forced by observed features such
186 as solar variability, volcanic aerosols, modification of the atmospheric composition (greenhouse gases
187 and aerosols) caused by human activities. These simulations go from 1850 and extend to the near
188 present (2014 in CMIP6). The AMIP-type simulations (hereafter referred to as "atmosphere-only
189 simulations"), on the other hand, can be used to assess the atmospheric response to forcings by
190 surface conditions (especially SSTs) in addition to changes in the composition of the atmosphere. The
191 period of availability of the atmosphere-only simulations is from January 1979 to December 2014.

192 A total of eight models are used in this study: CNRM (Centre National de Recherches Météorologiques),
193 IPSL (Institut Pierre-Simon-Laplace), E3SM (Energy Exascale Earth System Model), MIROC (Model for
194 Interdisciplinary Research on Climate), MOHC (Met Office Hadley Center), MRI (Meteorological
195 Research Institute), GFDL (Geophysical Fluid Dynamics Laboratory) and NCAR (National Center for
196 Atmospheric Research). The climatic variables are extracted over the period 1979–2014, and comprise
197 low cloud fraction, SST, atmospheric temperature, zonal and meridional wind, and relative humidity.

198 The number of simulations used per model is provided in table 2. It corresponds to the availability and
199 accessibility of the data at the time of research. In this study all ensemble members available for a
200 given model and experiment are averaged together when analysing mean patterns, but are considered
201 individually when computing correlations.

202

203 2.7 Definition of low clouds

204 Surface synoptic reports from which the ISD and EECRA archives derive are based on human observers'
205 estimates of the cloud fraction of low clouds (LC) as the part of the sky covered by clouds the base
206 height of which is typically below an altitude of 2 km. However, this category includes both stratiform
207 clouds (stratus and stratocumulus) and vertically extensive clouds (cumulus and cumulonimbus). Since
208 the present study is interested in stratiform clouds only, vertically extensive clouds (LC codes 1, 2, 3
209 and 9) have been excluded from LC observations (i.e., the corresponding cloud fraction is set to zero).
210 We retained LC code 8 (cumulus and stratocumulus with bases at different levels), thus contrary to
211 Schrage and Fink (2012), our LC statistics do not purely refer to stratiform clouds, although this is the
212 overwhelming cloud type for the region and the season. In EECRA, the two extended codes for
213 obscured sky conditions available in this data set (codes 10 and 11, i.e. fog and thunderstorms) have
214 not been considered (low cloud cover similarly set to zero). The cloud fraction initially expressed in
215 octas was converted to percent, and the arithmetic mean was computed to obtain monthly and
216 seasonal averages. In the ISD data set, some records are based on METAR reports, which classify cloud
217 cover in 5 broad categories. For ISD we therefore considered the occurrence of stratiform low clouds
218 by considering the presence of an extensive low cloud cover at the time of observation, defined as an
219 LC fraction greater than or equal to 5 octas (i.e. "broken" or "overcast" in the METAR cloud deck
220 reports). The LC frequency is then simply obtained as the percentage of low cloud observations divided
221 by the total number of synoptic reports at the station. This definition was retained for the ISD dataset
222 only.

223

224 Reanalysis products provide LC fraction data but the tropospheric depth over which low clouds are
225 considered differ between ERA5 and MERRA2. In ERA5, low clouds are defined as the integration of all
226 clouds found at pressure levels greater than 0.8 times the local surface pressure, i.e. below about 2 km
227 assuming a standard atmosphere. Importantly, ERA5 LC fraction does not distinguish stratiform from
228 vertically developed clouds, hence it is expected that in seasons when convection is active (outside the
229 JJAS season in the core study area) ERA5 LC fraction is positively biased relative to our station estimate
230 described above. In MERRA2, the LC fraction ("CLDLow" variable) is described as the maximum of the

231 total cloud fraction (convective and large scale) of any layer at or below 700 hPa (about 3km in a
232 standard atmosphere).

233
234 For CALIOP satellite data, the low cloud definition is the one retained in the GCM-Oriented CALIPSO
235 Cloud Product (GOCCP) (Chepfer et al., 2010). GOCCP was built from an algorithm designed to evaluate
236 the representation of clouds in climate models. Three categories of clouds are differentiated based on
237 pressure level (P): low level ($P > 680$ hPa), medium level ($680 < P < 440$ hPa) and high level ($P < 440$ hPa).
238 The retrieval steps are described by Chepfer et al. (2013). In this product, low clouds are characterized
239 by the cloud fraction at elevations below 3.2 km ($P > 680$ hPa). The LC fraction is calculated from the
240 CALIPSO simulation included in the second version of the Cloud Feedback Model Intercomparison
241 Project Observational Simulator Package (COSP) (Webb et al., 2017). Although these data can handle
242 multi-layered clouds, the presence of optically thick high clouds and those associated with deep
243 convection within the Intertropical Convergence Zone may partly mask low clouds (Chepfer et al.,
244 2010; Vaughan et al., 2009). For this reason, the difference with the definitions retained in synoptic
245 observations not only lies in the altitude of the top of the lower level, but also to the fact that in one
246 case the clouds are somehow observed "from below" and in the other case "from above".

247 The data from CALIOP, ISD and EECRA will serve as initial references for the evaluation of CMIP6 and
248 reanalyses. Each of these reference datasets has its own flaws: ISD and EECRA records have lots of gaps
249 and are only available at a limited number of stations, and in CALIOP stratiform low clouds can
250 sometimes be undetectable since they can be hidden by opaque higher clouds of convective origin.

251

252 2.8 Methods

253 Most analyses focus on the JJAS season, which is the dry season in most of WEA and shows the highest
254 frequency of stratiform low clouds (Dommo et al., 2018). JJAS long-term means at individual stations
255 are computed from all available observations (using only stations with at least 300 three-hourly
256 records). Both night- and daytime observations are used, since the CMIP6 data do not enable to
257 investigate the diurnal cycle. Although low clouds are more frequent at night, we checked that both
258 night- and daytime observations were present at the stations we used (i.e., the stations did not close
259 during the whole night), and that the general results of our study were not affected by mixing night-
260 and daytime records. However, observed ISD and EECRA low cloud monthly and seasonal means may
261 be slightly negatively biased because more observations are generally available at daytime (63% of the
262 records are within the time-span 0600-1500 UTC).

263 The inter-comparison of the data sets is first carried out over a broad area covering an extended Gulf
264 of Guinea area and the neighbouring African land areas (15°W–30°E, 20°S–20°N, figure 2). Then more
265 restricted analyses are produced focusing on WEA, using regional indices which will be defined below.
266 This part of the analysis has some limitations in CMIP6, since the relatively coarse spatial resolution of
267 the simulations (100–250km) do not enable a detailed spatial analysis.

268 Comparisons between the data sets are made using standard methods. To assess the agreement in the
269 spatial distribution of low clouds, pattern correlation coefficients are computed as well as bias and
270 root-mean-square error (RMSE). To that end, all products are linearly interpolated to the same
271 resolution, i.e. that of ERA5 (about 30 km). The agreement in temporal variations is examined by
272 plotting the mean annual cycle of low clouds and, for the atmosphere-only experiments, reanalyses
273 and observations, by analysing interannual variations using Pearson’s correlation coefficient. The
274 latter is also used to relate low clouds and SST variations. In addition, Taylor diagrams are plotted,
275 which enable to compare at the interannual time-scale the skills of different data sets (CMIP6 and
276 MERRA2) with respect to a reference time-series (ERA5), by combining correlations, centered RMSE
277 and standard-deviations.

278 Two regional low clouds indices are extracted over Gabon, depicting regions where the dry season low
279 cloud cover is the most persistent (figure 1), with coastal and inland locations respectively in order to
280 depict the zonal LC gradient (Dommo et al., 2018). Given the coarse definition of CMIP6 data and the
281 limited availability of synoptic stations, it was not possible to define customized indices reflecting the
282 exact topography, although the latter has some effect on LC patterns. The first index covers north-
283 western Gabon along the coast (9–11°E, 1°S–1.5°N) and the second one is located further inland over
284 north-eastern Gabon (11–13°E, 1.5°S–1.5°N). Each includes three stations from the ISD and EECRA
285 databases, namely Libreville, Cocobeach and Lambaréné (NW-Gabon), and Makokou, Mitzic and
286 Lastoursville (NE-Gabon). Seasonal (JJAS) means for individual years are computed first at station level
287 (based on days with at least 4 three-hourly records, and provided that half the days in a season have
288 data), then the time-series for each station is standardised, and finally a regional average is computed.
289 If in a given year only one station is available, then the average is set to missing.

290 An SST index is also computed over the region 5–13°E and 2–9°S, i.e. off the coasts of Gabon and
291 Congo-Brazzaville, south of Cape Lopez. This corresponds to the part of the equatorial Atlantic
292 upwelling area (“cold tongue”) which shows the largest amplitude (>3.5°C) in the SST annual period
293 (Merle et al., 1980). However, this index is representative of JJAS SST variations over a much larger
294 area covering most of the Eastern Equatorial Atlantic (Servain and Merle, 1993 - not shown).

295 In order to describe atmospheric stability, a key feature in the development of low clouds (Slingo, 1987;
296 Klein and Hartmann, 1993; Hu et al., 2008; Sun et al. 2011), the Lower-Tropospheric Stability index
297 (LTS) defined by Klein and Hartmann (1993) is used. It is computed over Gabon (10–12°E, 3°S–1°N) as
298 the difference between the potential temperature at 700 and 925 hPa. The 925 hPa pressure level was
299 used instead of 1000 hPa because over land, 1000 hPa temperature is not defined in all the models.

300

301 3. Results

302

303 3.1 Climatology of low level clouds

304

305 The JJAS mean low cloud fraction is first examined over the larger region (Gulf of Guinea and nearby
306 African landmass) (figure 2). CALIOP data shows a major contrast between the oceanic areas, where a
307 high to very high LC fraction is observed (40–85%), especially off the coast of Southern Angola, and the
308 land areas where LC fraction is generally below 20%. As an exception to the land areas, the coastal
309 regions from Sierra Leone to Northern Angola show a higher LC fraction, with a distinct maximum in
310 Gabon (30–70%). This maximum decreases inland, but the LC fraction in the northern Democratic
311 Republic of Congo is still above 20%. The two reanalysis products and the CMIP6 coupled simulations
312 all display high pattern correlations with CALIOP (figure 2, lower right corners). This merely reflects the
313 land-ocean contrast, always well replicated, but it is easy to see that both the oceanic and land patterns
314 often notably differ from the CALIOP satellite estimates. In ERA5 for instance, while the oceanic LC
315 fraction agrees relatively well with satellite data (as found by Koseki and Imbol Koungue, 2021), on the
316 land areas bordering the Gulf of Guinea, the LC fraction is very high, and even over the inland
317 (northern) part of the Congo Basin, it often exceeds 40%. This is likely due to the fact that in ERA5, low
318 clouds include convective clouds with a low cloud base. MIROC also portrays a high LC fraction over
319 the Congo Basin, with almost no difference with the coastal regions. By contrast, an overall negative
320 bias is found in some products, especially MERRA2 reanalysis and CNRM. The IPSL simulations are
321 among the most skilful ones, both in terms of bias and spatial patterns. On the whole however, most
322 CMIP6 simulations tend to underestimate LC fractions over coastal areas north of 10°S and the SE
323 tropical Atlantic.

324

325 When using the atmosphere-only simulations instead of the coupled ones (figure 3), most models still
326 underestimate LC fractions. However, there is a substantial increase in oceanic and coastal LC fraction
327 in the IPSL, E3SM, MOHC and CNRM models. There is also a marginal increase in many correlation
328 coefficients, but the geographical patterns are not strongly altered. Only MRI shows a significant

329 correlation increase (from 0.74 to 0.87), which suggests that in this model the coupling critically affects
330 the simulation of LC.

331

332 In order to document LC fraction over Gabon, JJAS averages for the two above-defined regional indices
333 are computed (see figure 1 for their location). Synoptic observations are now added and serve as
334 reference for the other datasets. For NW-Gabon (figure 4a), observed LC frequency (ISD) / LC fraction
335 (EECRA) are both very high (73–74%). CALIOP satellite estimates are somewhat lower (62%), possibly
336 because in some occasions low clouds may be obscured by an upper dense cloud layer. The two
337 reanalyses strongly disagree with ERA5 being very close to observation (70%), while MERRA2 shows
338 unrealistically low LC fraction (22%) in agreement with the large bias seen in figure 3. All the CMIP6
339 coupled simulations (figure 4, light blue bars) underestimate LC fraction. The range is wide however,
340 with CNRM and E3SM cloud fraction being as low as 26% and MIROC reaching 52%. It is noteworthy
341 that all the atmosphere-only simulations (figure 4, dark blue bars), with the exception of MIROC, yield
342 smaller LC fraction biases. The IPSL model shows a mean over NW-Gabon of 75%, very close to
343 observations, and both MOHC and E3SM have LC fractions near 60%, compared to about 30% in their
344 respective coupled simulations. This suggests that the ocean-atmosphere interactions are important
345 components of LC simulation, and that incorrect feedbacks of clouds or atmospheric dynamics on the
346 state of the upper ocean layers are the potential cause of the LC underestimation over the South
347 Atlantic Ocean and nearby land areas.

348

349 For NE-Gabon (figure 4b), quite similar conclusions can be reached. Satellite (CALIOP) and in-situ
350 observations (ISD and EECRA) are very close to each other, with LC fraction / frequency around 60%,
351 i.e. slightly less than in NW-Gabon. ERA5 shows a marginal negative bias, but MERRA2 cloud fraction
352 remains very low (19%). Again, CMIP6 models generally underestimate LC fraction, although
353 atmosphere-only simulations perform a bit better than coupled simulations. The ranking of the models
354 in terms of skill is not the same as for NW-Gabon. For instance, the IPSL model shows a too strong
355 inland decrease of LC fraction. However, the coarse spatial resolution of the models is not fully
356 adequate to depict such gradients, partly controlled by topography, which is oversimplified in global
357 models.

358

359 The LC annual cycle in the two regions is plotted in figure 5, for CALIOP, synoptic observations and
360 reanalyses, compared to CMIP6 coupled (panels a-b) and atmosphere-only simulations (panels c-d).
361 Synoptic observations (ISD and EECRA) display a strong annual cycle in NW-Gabon. The JJAS season
362 clearly stands out as the period with the highest LC fraction. Low clouds are less frequent in the wet
363 months, i.e. from October to May. The CALIOP annual cycle agrees well with synoptic observations,

364 although in the cloudy season, the LC fraction is underestimated, and the peak is shifted to July instead
365 of August in both ISD and EECRA observations. Reanalyses deviate markedly. While for ERA5 the JJAS
366 mean is close to observations, the LC fraction during the rest of the year is too high (45–65% from
367 October to May) compared to synoptic records (20–40%). This is due to the fact that convective clouds
368 with low cloud bases are included in the ERA5 LC fraction. By contrast, the MERRA2 reanalysis shows
369 an underestimation of LC all year round, especially in JJAS as documented above.

370
371 CMIP6 coupled simulations (figure 5a) display highly dissimilar patterns. MIROC fails to show any
372 realistic annual cycle, with high values outside the JJAS season. This suggests that, as in ERA5, MIROC's
373 low clouds include deep convective clouds, which are dominant outside the JJAS season. This feature
374 could also explain the high LC fraction over the northern Congo Basin in JJAS in both MIROC and ERA5
375 (figure 2), since convection is relatively active over this region at this time of the year. MIROC's LC
376 fraction unexpectedly drops in August. However, most of the models are able to reproduce an austral
377 winter LC maximum, but it is systematically too weak, sometimes too early (July in CNRM) or more
378 often, too late (September in MRI and E3SM) compared to synoptic reports. For most models, it is the
379 onset of the cloudy season (i.e. the strong increase in LC fraction in June) which is critical, with low
380 clouds developing too slowly in the models. Wet season LC fractions are much better reproduced by
381 most models, except IPSL, which on the contrary has a dry season maximum closest to observations,
382 though delayed.

383
384 Compared to coupled simulations, CMIP6 atmosphere-only simulations (figure 4c) better agree with
385 observations, both in terms of timing and amplitude of the annual cycle. The quick increase of LC
386 fraction between May and June is much better reproduced by the atmospheric models, although still
387 a bit weak, except in MOHC or IPSL. However, the peak of LC is still too early in some models (MOHC,
388 GFDL) or too late in others (E3SM, NCAR, MRI). Notably, MIROC's annual cycle is not improved when
389 compared to the coupled version. On the whole, these results confirm that the atmosphere-ocean
390 coupling is key for the accurate reproduction of LC in the region.

391
392 The NE-Gabon annual cycle displays features similar to those of NW-Gabon, except with a smaller
393 amplitude (figure 5b–d). In synoptic observations (ISD and EECRA), both the austral winter maximum
394 is a bit lower (about 65% in July and August) and the wet season cloud fraction a bit higher (30–40%).
395 CALIOP cloud fraction is very close to observations in the cloudy season, but lower (20–30%) in the wet
396 season. Both reanalyses again display too weak annual cycles. Similarly, CMIP6 coupled simulations
397 (figure 5b) do not reproduce well the austral winter LC increase, and their wet season cloudiness is
398 also too low. An improvement is found in the atmosphere-only simulations (figure 5d), which show a

399 larger amplitude in their annual cycle, but the LC fraction is still too low in most months and most
400 models.

401

402 3.2 Interannual variability of low clouds

403

404 The interannual variations of the JJAS low clouds in the period 1979-2014 are examined for the two
405 Gabon regional indices, in the observation and in the ERA5 reanalysis. The MERRA2 reanalysis is not
406 used given its strong underestimation of LC fraction during this season. Since CALIOP data are available
407 over a short period of time (2006-2014) only, with few years having simultaneous synoptic records,
408 they are not used here either. The many missing observations in the ISD and EECRA data result in highly
409 discontinuous time-series, especially for NE-Gabon. Nevertheless, ERA5 and observations display
410 variations that are largely in phase (table 2). For NW-Gabon, ERA5 correlates at 0.78 with ISD
411 (significant at $p < 0.001$, 26 years) and at 0.77 with EECRA (significant at $p < 0.001$, 19 years). For NE-
412 Gabon, ERA5 is also strongly correlated with both EECRA (0.82, significant at $p < 0.001$, 18 years) and
413 ISD cloud frequency, although for the latter, the number of years available is small (10 only). These
414 results show that ERA5 performs well at reproducing interannual variations of low clouds over Gabon,
415 despite the fact that this variable is not constrained by assimilated cloud observations and therefore
416 entirely simulated by the ECMWF model. In NW-Gabon (figure 6), most years with an abnormally high
417 LC fraction (e.g. 1982, 1983, 1992, 1994, 2005) and those with a low LC fraction (e.g., 1984, 1988, 1989,
418 1995, 1996, 1999, 2007) show a reasonable agreement between ERA5 and synoptic observations. The
419 year 1984 is known as a highly singular dry season, with out-of-season heavy convective rains in Gabon,
420 which are consistent with the lower frequency of stratiform low clouds (Buisson, 1984). Interannual
421 variations in NE-Gabon are fairly similar (not shown), though the observed time-series are highly
422 discontinuous. The NE-Index correlates with the NW-index at 0.74 (ISD, 11 years), 0.71 (EECRA, 17
423 years) and 0.98 (ERA5, 36 years).

424 In the next step, we examine the ability of the CMIP6 models to reproduce the interannual variations
425 of the LC over the same two regions of Gabon. Solely the atmosphere-only simulations can be analysed
426 since the coupled simulations all have their own internal variability. The ERA5 indices are used as the
427 reference because as demonstrated above, they agree fairly well with observed variations, and they
428 have continuous time-series over the period 1979–2014. The MERRA2 data have been included in the
429 assessment. In NW-Gabon (figure 7a), the CMIP6 models show contrasted skills. Three models, CNRM,
430 IPSL and GFDL, stand out by their high correlations with ERA5 (0.64 to 0.72, all significant at $p < 0.001$),
431 with a similar and relatively low RMSE (around 3.9%). However, while IPSL and GFDL standard-
432 deviations match that of ERA5, it is too low in CNRM. A lower correlation is found for NCAR (0.45),

433 while all other models (MRI, E3SM, MOHC) show insignificant or even negative correlations with ERA5.
434 The MERRA2 reanalysis is characterised by a very small standard-deviation, reflecting the large
435 negative bias as discussed above, and its correlation with ERA5 is only modest (0.45).

436 Overall, the same observations and ranking of models can be made for the NE-Gabon index (not
437 shown). However, correlations with ERA5 are generally lower than in NW-Gabon, and the RMSE is
438 generally higher. Again, GFDL stands out as the model with the best skill.

439

440 3.3 Relationships with sea-surface temperature

441

442 The inferior performance of the coupled simulations compared to atmosphere-only simulations point
443 to a key role of oceanic dynamics in the adequate simulation of low clouds. Dommo et al. (2018) also
444 suggest that the seasonal occurrence of cool SST off Gabon is instrumental in low cloud genesis. This
445 section thus analyses SST patterns and variability over the South Atlantic Ocean. In Figure 8, the JJAS
446 mean SST is mapped for the eight CMIP6 coupled models (panels b to i) and for the ERA5 reanalysis as
447 a reference (panel a). ERA5 distinctly shows a northward SST gradient, with cold water ($<20^{\circ}\text{C}$) along
448 the coast of Namibia and southern Angola (ca. $15\text{--}20^{\circ}\text{S}$), associated with the Benguela Current and
449 coastal upwelling, and warm water north of the equator ($>26^{\circ}\text{C}$). A zonal band of relatively cool water
450 ($23\text{--}25^{\circ}\text{C}$) is found slightly south of the equator, denoting the Equatorial Atlantic upwelling zone (cold
451 tongue area). The temperature does not exceed 23°C along the coasts from northern Angola to Cape
452 Lopez in Gabon. In all the CMIP6 models, SSTs are biased high in the southeast Atlantic Ocean, including
453 along the coasts of Congo-Brazzaville and Gabon. Likewise, the equatorial cold tongue is missing in
454 most models, or it is too weak and does not extend far enough to the east, like in MIROC or GFDL. Of
455 all the CMIP6 models, MRI and to some extent IPSL seem to best reproduce SSTs over the Atlantic and
456 along the Gulf of Guinea coasts during JJAS, although temperatures are overestimated by about 2°C
457 on average. In MRI the equatorial upwelling extends well towards the coasts of Gabon and Congo-
458 Brazzaville, where the ocean temperature drops to 23°C as in ERA5.

459 In order to better describe the SST along the Gabonese coast, a regional index is extracted for the area
460 boxed in blue on figure 8a. The annual cycle is plotted in figure 9 to find out whether the poor
461 replication of the JJAS SST in CMIP6 is a result of a flawed seasonal cooling. All the models overestimate
462 SST off the southern coast of Gabon except for – to some extent – MRI. The austral winter cooling is
463 reproduced by all models, but it is noteworthy that it starts too late and is too weak. While in ERA5 the
464 warmest water is found in March (29°C), with a strong cooling starting after April, in most models the
465 SST drops too late and too slowly. Simulated minimum temperature is generally found in August, a bit

466 late compared to ERA5, and is not cold enough (positive bias of 3–4°C). The models that are best able
467 to reproduce the equatorial upwelling (IPSL and especially MRI) are the only ones to show a quick SST
468 drop from May to July which almost matches that of ERA5, although the minimum austral winter
469 temperature is still overestimated.

470 Figure 10 shows the correlation between interannual variations of LC fraction (JJAS average) in NW-
471 Gabon and SST at each grid point, within each data set (e.g., ERA5 cloud fraction with ERA5 SST, CNRM
472 cloud fraction with CNRM SST etc.). For ERA5 (figure 10a), the correlation is generally negative over
473 the Equatorial Atlantic Ocean, which indicates that the years showing a high LC fraction in Gabon
474 coincide with cooler ocean temperature than usual. Reciprocally, anomalously warm years such as
475 1984, 1988, 1995, 1998, 1999, 2003 and 2007 generally coincide with less low clouds in Gabon (figure
476 6). The correlation coefficients exceed 0.75 (significant at $p < 0.001$) in the Eastern Equatorial basin. The
477 correlation maps for LC fraction in NE-Gabon display similar patterns to those of NW-Gabon except
478 that the correlations are generally slightly lower. The use of the SST index extracted off the coasts of
479 southern Gabon and Congo-Brazzaville confirms the very strong negative correlation with ERA5 LC
480 fraction in the two regions (NW-Gabon: -0.81, NE-Gabon: -0.76).

481 CMIP6 coupled simulations (figures 10b-i) display correlation patterns with NW-Gabon LC fraction that
482 differ largely between models. Two of the eight models, MIROC and NCAR, show non-significant
483 correlations (either slightly positive or slightly negative). The others have negative and significant
484 correlations ($p < 0.05$) in agreement with ERA5, but the patterns and intensity are sometimes quite
485 different from those observed. In most of them (IPSL, E3SM, MOHC, GFDL), the highest negative
486 correlations are generally found in the equatorial upwelling area south of the equator. They more or
487 less expand eastward and southward to the African coast from Gabon to Namibia. This pattern is
488 relatively close to that observed from ERA5 data. For NW-Gabon, E3SM and GFDL (figures 10d & 10h)
489 clearly show the strongest negative correlations (< -0.75), which best agree with ERA5, though some
490 inaccurate positive correlations are found along the West African coast and in the southwestern
491 Atlantic. The GFDL negative correlations tend to get a bit weaker for NE-Gabon (not shown). MRI
492 exhibits correlations which are quite uniform but weak, and CNRM displays an unrealistic pattern.

493 Over the period 1979–2014, there is a significant warming trend over the South Atlantic Ocean in all
494 the eight coupled models but GFDL (not shown). When the linear trend is removed, the correlations
495 are generally slightly enhanced for the models which were already showing an SST-low clouds
496 relationship. Although difficult to transpose to climate change issues, this suggests that a warming
497 trend may not necessarily result in less low clouds over Gabon.

498 Figure 11 shows the scatter-plots of NW-Gabon LC fraction vs. SST off southern Gabon, where each
499 dot is the JJAS average of a given year, with colours and symbols referring to each of the 8 coupled
500 models (with black stars showing ERA5). An important feature is that the LC bias does not necessarily
501 scale with the SST bias. In other words, the models that most strongly underestimate LC are not
502 necessarily the ones showing the highest SST. For instance, compared to MIROC, MRI only weakly
503 overestimates SST, but has a larger low cloud bias than MIROC. In terms of interannual correlations
504 between LC and SST, the models perform inconsistently. Regression lines are plotted only for the
505 models that show a statistically significant linear relationship between interannual variations of LC and
506 SST. Three models (E3SM, GFDL and IPSL) display very strong negative correlations, as for ERA5. The
507 others either underestimate the relationship or completely miss it. Models that exhibit unsuitably low
508 interannual SST variations tend to miss the relationship with the LC fraction (e.g., CNRM, MIROC,
509 NCAR). GFDL and E3SM, which have the strongest negative correlation with SST (-0.78 and -0.93,
510 respectively) also displays the largest interannual variability, with SSTs varying between 25 and 28.5°C,
511 a range similar to that of ERA5, although (like in other models) SSTs are much too high. However, the
512 correlation between low cloud and SST is unrelated to biases: while MRI has smaller biases compared
513 to E3SM, its correlation is much lower than E3SM.

514 In order to further understand the origin of the poor performance of several models, the same
515 correlation maps as in figure 10 are produced using the atmosphere-only simulations instead of the
516 coupled ones (figure 12). Almost all the models now reproduce a negative correlation between LC
517 fraction and SST in the Equatorial Atlantic. Compared to ERA5, the spatial pattern and amplitude of
518 the correlation are very accurate in the CNRM, IPSL, MOHC, E3SM and GFDL models. Correlations are
519 a bit too weak in NCAR and MRI, while MIROC portrays a positive correlation, confirming that low
520 clouds captured over Gabon in this model are mainly convective clouds. These results show that much
521 of the flaws in the relationship between SST and cloud fraction in the coupled simulations arise from
522 faulty ocean-atmosphere feedbacks.

523 3.4 Relationships with atmospheric fields

524 In order to determine whether the SST-cloud relationship involves variations in atmospheric stability,
525 a lower-tropospheric stability index (LTS) is extracted over Gabon. The scatter-plot of NW-Gabon LC
526 fraction versus LTS shows a very strong interannual correlation ($r=0.91$) in ERA5 (figure 13). As
527 expected, increased stability is key to the development of a stratiform low cloud cover. This
528 relationship is reproduced by a majority of models. Three of them (IPSL, E3SM and NCAR) show
529 correlations similar to ERA5. Three others have much weaker but significant ($p<0.05$) correlations:
530 MIROC, MOHC and MRI. No relationship is found for CNRM and GFDL. Interestingly, although stability

531 is supposed to be largely constrained by SST, the models which skilfully reproduce the relationship
532 between LC fraction and stability are not always the same as those which are good at simulating the
533 relationship with SST. E3SM and IPSL reproduce both relationships. By contrast, NCAR and MIROC show
534 a good fit between low clouds and stability, but not with SST. This suggests that in these models
535 climatic forcings other than SST (possibly mid-tropospheric air temperature) have a dominant control on
536 stability. Conversely, low clouds variability in GFDL is related to SST, but it fails to show any clear
537 relationship with LTS. Overall, these results indicate that the poor simulation of low clouds in the
538 CMIP6 models may be due to a variety of reasons. While the incorrect simulation of SST and association
539 with low clouds is a key feature, purely atmospheric issues are also at play in many models.

540 While the detailed assessment of these failures is beyond the scope of this paper, figure 14 highlights
541 some atmospheric variables which show a significant relationship with LC fraction over NW-Gabon in
542 ERA5 (top panels). Near-surface winds display positive correlations in the Gulf of Guinea area north of
543 the equator, particularly the Bight of Bonny (both U and V), indicative of an enhanced southwesterly
544 monsoon flow in years with an increased cloud fraction. A stronger monsoon flow north of the equator
545 was found to result from an SST drop in the cold tongue area around the start of the first Guinean rainy
546 season (Leduc-Leballeur et al. 2013; Meynadier et al. 2016). Therefore, the positive correlations
547 between LC fraction and U1000 and V1000 reflect the role of SST on both winds and cloudiness.
548 However, at 850 hPa the correlations with the meridional wind flow turn negative (figure 14),
549 suggesting that the monsoon depth is reduced when the LC fraction is high. This pattern, together with
550 the stronger near surface meridional winds, is indicative of stronger but shallower monsoon flow. This
551 combination is only possible in an environment of higher vertical stability, where turbulent mixing is
552 suppressed and where moisture is concentrated in a shallower layer to allow a more persistent
553 stratiform cloud cover. Potentially, increased surface fluxes due to the higher wind speeds further
554 support this process.

555 At 700 hPa (above the monsoon flow), a weak positive correlation between LC and temperature is
556 found over Gabon and neighbouring regions (figure 14, top right panel). Together with the negative
557 correlation with surface temperature and SST, this is in line with the strong relationship found above
558 between LTS and low clouds, since a warmer mid-troposphere (colder lower-troposphere) increases
559 low-level stability.

560 By extracting regionally-averaged indices representative of these relationships (yellow boxes on top
561 panels of figure 14), it is found that the models unevenly reproduce the relationships found in ERA5
562 (central panels). In particular, the connection with meridional wind is often poorly represented. E3SM

563 and NCAR perform best in this respect. Only E3SM, MOHC and MRI consistently reproduce the
564 relationships with U1000, V1000 and V850.

565 In order to find out whether these atmospheric dynamics are related to SST variations, partial
566 correlations are computed between low clouds and the same atmospheric indices, after removing the
567 effect of Eastern Equatorial Atlantic SST (figure 14, bottom panels). In ERA5, the correlation with
568 meridional winds (V1000) becomes very low, indicating that the above wind signal was strongly
569 associated with SST-induced north-south temperature gradients. The correlation with V1000 becomes
570 generally weaker in the models as well, though still significant in E3SM, MRI and NCAR, which for the
571 latter two is no surprise given their poor skills at reproducing SST variations. Note that the near-surface
572 zonal wind flow, by contrast, remains in many models significantly correlated to low clouds after
573 removing the effect of SST, suggesting that other features (possibly land surface warming) also drive
574 the strength of the westerlies. The fact that these partial correlations remain significant while they are
575 not any more in ERA5 is also due to the generally underestimated relationship with SST in several
576 models. The same remarks apply to V850.

577 Partial correlations with 700 hPa temperature (figure 14, bottom-right panel) are significant, and even
578 stronger than the total correlations, in both ERA5 and several models. This shows that mid-
579 tropospheric warming has a distinct effect on the occurrence of low clouds. It is conceivable that this
580 variable is influenced by processes such as advection or longwave cooling associated with variations in
581 free-tropospheric water vapour or high-level clouds (see e.g. discussions in Andersen et al., 2020).

582

583 4. Conclusions

584 Stratiform low clouds are a recurrent feature of the Southeast Atlantic Ocean. In austral winter, they
585 extend over southern West Africa and Western Equatorial Africa, and mean cloud fractions of more
586 than 60–70% are found over Gabon and southern Congo-Brazzaville. This extensive low cloud cover
587 during the dry season is suspected to play a key role in the presence of a rainforest over WEA, by
588 reducing solar radiation, daytime temperatures and hence water demand. The present paper aimed
589 at assessing the ability of reanalysis products (MERRA2 and ERA5) and CMIP6 models to simulate these
590 low clouds and their drivers, by focusing on mean patterns and interannual variability. CALIOP satellite
591 data and ground observations at synoptic stations were used as reference.

592

593 Over the broader region (Equatorial Atlantic and Tropical Africa), the spatial patterns of mean low
594 cloud occurrence as depicted by CALIOP data are reasonably well reproduced by CMIP6 models, ERA5
595 and MERRA2 reanalyses. However, the mean cloud fraction is severely underestimated in MERRA-2

596 and in several models, as earlier shown for CNRM for instance (Voldoire et al. 2019). In WEA in
597 particular, most data sets struggle to correctly reproduce the amplitude of the annual cycle and
598 underestimate the JJAS low cloud fraction, with respect to synoptic reports at stations in Gabon.
599 Although MERRA-2 reanalysis shows very good skill in reproducing precipitation and winds in Central
600 Equatorial Africa (Hua et al. 2019), it severely underestimates low clouds. An underestimation of the
601 total cloud fraction in MERRA2 was found for China by Feng and Wang (2019), leading to an
602 overestimation of solar radiation. By contrast, ERA5 reanalysis is fairly accurate in simulating low
603 clouds in WEA during the austral winter, but produces too many low clouds in the rest of the year,
604 probably due to the fact that convective clouds are not discriminated from stratiform clouds in ERA5
605 as done in this paper for the reference station observations.

606

607 Interestingly, the underestimation of low clouds is generally reduced in atmospheric models forced by
608 observed SST compared to coupled ocean-atmosphere models. This suggests that part of the
609 inaccuracies in low cloud simulations is related to unrealistic simulated SSTs. The seasonal
610 development of low clouds in WEA is primarily associated with the surface cooling of the Equatorial
611 Atlantic Ocean between April and July. This cooling is delayed and too weak (2–4°C in most models,
612 instead of 5–6°C) in the CMIP6 coupled models. Richter and Tokinaga (2020) also noted the warm bias
613 in the Equatorial Atlantic in CMIP6, with little improvement upon CMIP5 simulations, and attributed it
614 to the response to wind forcing being too weak. This warm bias reduces the stability of the lower
615 troposphere, which may account for the underestimation of stratiform low clouds. This is in agreement
616 with the observations by Cesana et al. (2012) on the links between SST and low clouds. However, we
617 note that over WEA, the inter-model variations in the low cloud biases do not necessarily scale with
618 their respective SST biases, suggesting that additional factors are at play.

619

620 At the interannual timescale, ERA5 variations of low cloud cover match reasonably well those of
621 observed data. These variations are inconsistently reproduced by the atmosphere-only simulations
622 forced by observed SSTs. The GFDL, IPSL and CNRM AMIP-type models show the best correlations
623 ($r \sim 0.65$ – 0.70 for NW-Gabon over the period 1979–2014). ERA5 data reveal that these interannual
624 variations in low cloud cover are strongly related to SST over a large part of the Equatorial Atlantic
625 Ocean, with correlations exceeding 0.7 in the equatorial upwelling area and off the coasts of Gabon
626 and Congo-Brazzaville. Some models underestimate this relationship, and others completely miss it.
627 The accuracy of the correlation between SST and low cloud variations is only loosely related to the
628 mean biases of the models. Several models display a mean JJAS SST off Gabon exceeding 26°C, an often
629 used threshold for deep convection (Zhang, 1993), whereas in the observation SST over the same
630 region is close to 23.5°C. Yet some of these models, especially E3SM, adequately simulate a strong

631 relationship between low clouds and SST. However, models whose SSTs are always above 26°C fail to
632 show any strong relationship with low clouds (yet some of them display fairly high and variable LC
633 fraction), suggesting that above this threshold low cloud formation obeys to other forcings in these
634 models.

635

636 A preliminary analysis of atmospheric patterns associated with interannual low cloud variations has
637 been carried out in order to suggest possible explanations for the poor low cloud simulations, in
638 addition to the SST biases. Interannual variations of lower-tropospheric stability (LTS) are strongly
639 correlated to low cloud fraction ($r=0.91$ over Gabon in ERA5). Mean LTS is markedly underestimated
640 in all coupled CMIP6 models, mainly as a result of too high SSTs. While the relationship of LTS with low
641 clouds is correctly simulated by half of the models, others display correlations much lower than in ERA5
642 or even fail to show any relationship. In some cases (e.g., CNRM, MIROC), this reflects the poorly
643 simulated SST-low cloud relationship. In GFDL however, while the SST forcing on low clouds is well
644 reproduced, the relationship with LTS is not, suggesting that in this case the mid-tropospheric
645 temperature fields are faulty.

646

647 ERA5 correlations actually show that low cloud cover over WEA is not only controlled by SST. Surface
648 zonal winds and 700 hPa temperature, partly independent of SST, exert secondary controls on
649 interannual variations of low cloud occurrence. Only about half of the CMIP6 models reproduce these
650 controls. Reanalysis data analysed by Neupane (2016) indicate that the strength of zonal circulation
651 over WEA is controlled by west-east temperature gradients, hence by Congo Basin temperatures in
652 addition to Equatorial Atlantic SST. Among other parameters, biomass-burning aerosols are suspected
653 to play a role in low cloud fraction over the South-East Atlantic Ocean, likely through an additional
654 radiative heating generated by smoke above the low-level clouds, which increases the stability of the
655 low-level inversion, a feedback which is not well represented in many CMIP6 models (Lu et al., 2018;
656 Mallet et al., 2021). However, over WEA, this effect seems moderate only (3-5 % increase of simulated
657 low cloud fraction over southern Congo-Brazzaville when aerosols are activated in the models,
658 according to Mallet et al. 2020).

659

660 On the whole, the above results show that the models' imperfect simulation of WEA low clouds has
661 different origins, though realistic SSTs are a key component. Even if biases in mean patterns are not
662 always deterrent to a fair simulation of interannual variations and associated forcing mechanisms, an
663 improved simulation of the coupled ocean-atmosphere dynamics in the region would be key for
664 reliably assessing future low cloud trends over WEA as a result of global warming. Further work also

665 needs to be carried out on the within-season changes in low cloud occurrence and their forcing
666 mechanisms.

667

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669

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850 List of tables

851 Table 1: Datasets used in the study together with the corresponding low cloud definition.

852

853 Table 2: Correlations between interannual variations (1979–2014) of JJAS low cloud cover in ERA5,

854 ISD and EECRA. All correlations are significant at $P < 0.01$.

855

856 Table 1: Datasets used in the study together with the corresponding low cloud definition.

857

Data base/ Model	Spatial scale (atmosphere)	Retained period	Type of data	# ensemble members (coupled/ atmosphere-only)	Definition of low clouds
CALIOP	200km	2006–2019	Satellite (lidar)	-	LC fraction (levels >680hPa)
ISD	Synoptic stations	1979–2014	Weather observations	-	LC frequency (<2000 m)
EECRA	Synoptic Stations	1979–2009	Edited weather observations	-	LC fraction (<2000 m)
ERA5	30km	1979–2014	Reanalysis	-	LC fraction (levels >0.8 surface pressure)
MERRA2	50km	1980–2014	Reanalysis	-	LC fraction (levels >700hPa)
CNRM	250km	1979–2014	Simulations	3/1	LC fraction (levels >680hPa)
IPSL	250km	1979–2014	Simulations	3/1	
E3SM	100km	1979–2014	Simulations	3/3	
MIROC	250km	1979–2014	Simulations	1/1	
MOHC	250km	1979–2014	Simulations	1/1	
MRI	100km	1979–2014	Simulations	1/1	
GFDL	100km	1979–2014	Simulations	1/1	
NCAR	100km	1979–2014	Simulations	1/1	

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859

860 Table 2: Correlations between interannual variations (1979–2014) of JJAS low cloud cover in ERA5,
 861 ISD and EECRA. All correlations are significant at $P < 0.01$.

862

	NW-GABON		NE-GABON	
	R	Number of years	R	Number of years
ISD vs. EECRA	0.95	17	0.93	11
ERA5 vs. ISD	0.78	26	0.84	10
ERA5 vs. EECRA	0.77	19	0.82	18

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867 List of figures

868

869 Figure 1: Map of Western Equatorial Africa with the surface stations extracted from the ISD (a) and
870 EECRA (b) databases to compute low cloud statistics. Colour dots: mean JJAS low cloud frequency (a)
871 and low cloud fraction (b), in percentages. Red boxes border the areas for the LCC regional indices.

872 Figure 2: JJAS mean low cloud fraction (in %) for CALIOP (a), ERA5 (b), MERRA2 (c) and CMIP6 coupled
873 simulations: CNRM (d), IPSL (e), E3SM (f), MIROC (g), MOHC (h), MRI (i), GFDL (j), NCAR (k). Means are
874 computed over the period 1979–2014 (1980–2014 for MERRA2). In the boxes, r is the pattern
875 correlation with CALIOP and b is the mean bias (in % cloud fraction).

876 Figure 3: Same as figure 2 but for CALIOP (a) and CMIP6 atmosphere-only simulations from CNRM (b),
877 IPSL (c), E3SM (d), MIROC (e), MOHC (f), MRI (g), GFDL (h), NCAR (i).

878 Figure 4: JJAS mean low cloud cover over NW Gabon (a) and NE Gabon (b). See table 1 for the definition
879 of low cloud cover and the period used for computation in each dataset.

880 Figure 5: Mean annual cycle of low cloud cover over NW Gabon (a, c) and NE Gabon (b, d). CMIP6
881 coupled simulations are displayed in (a) and (b), and atmosphere-only simulations in (c) and (d).

882 Figure 6: Interannual variations of JJAS low cloud cover between 1979 and 2014 in NW Gabon in ERA5
883 reanalysis (LC fraction) as well as in ISD (LC frequency) and EECRA (LC fraction) observations.

884 Figure 7: Taylor diagram of JJAS 1979–2014 NW-Gabon low cloud fraction in MERRA2 and CMIP6
885 atmosphere-only simulations, with ERA5 as the reference. Black dotted lines: correlation coefficients.
886 Blue dotted lines: standard-deviations. Green lines: RMSE.

887 Figure 8: JJAS mean SST (1979–2014, °C) over the South Atlantic Ocean in ERA5 (a) and CMIP6 coupled
888 simulations: CNRM (b), IPSL (c), E3SM (d), MIROC (e), MOHC (f), MRI (g), GFDL (h), NCAR (i). The
889 location of the Gabon SST index is shown on panel (a).

890 Figure 9: Mean annual cycle (1979–2014) of SST over the region [9–2°S, 5–13°E] in the Atlantic Ocean
891 southwest of Gabon (boxed area on figure 8a): ERA5 reanalysis and CMIP6 coupled simulations.

892 Figure 10: Internal correlations between interannual variations (1979–2014) of JJAS SST and low cloud
893 cover in NW-Gabon, in ERA5 and in each CMIP6 coupled model. Values above 0.33 / below -0.33 are
894 significant at $P < 0.05$.

895 Figure 11: Scatter plot of LC fraction in NW-Gabon versus SST over the Atlantic Ocean southwest of
896 Gabon [9–2°S, 5–13°E], for ERA5 and for each of the 8 CMIP6 coupled models. Each marker is the JJAS

897 mean of a given year. Regression lines are shown when the cloud fraction significantly correlates
898 ($p < 0.05$) with SST.

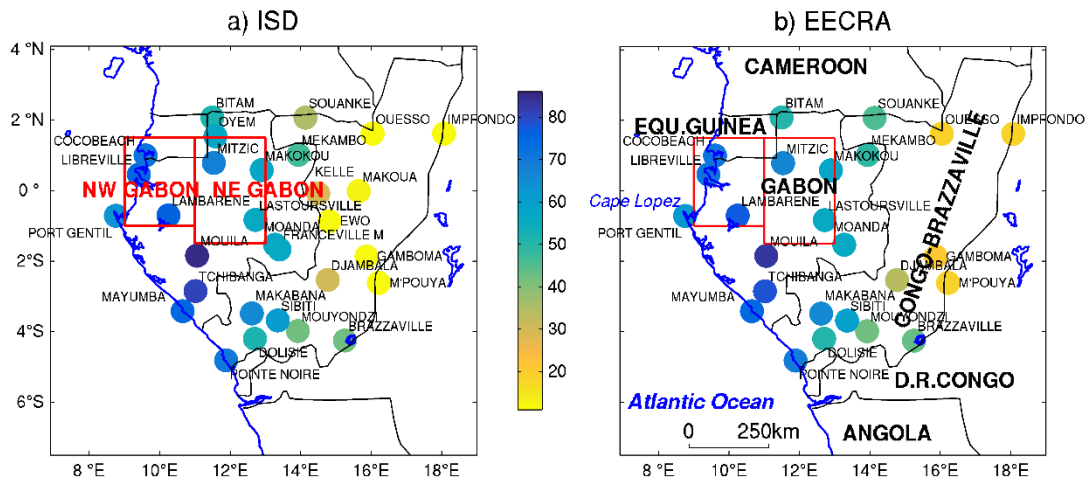
899 Figure 12: Same as figure 10 but for CMIP6 atmosphere-only simulations

900 Figure 13: As in figure 11 but for LC fraction in NW-Gabon versus Lower-Tropospheric Stability (LTS)
901 between 925 and 700 hPa over Gabon (10-12°E, 3°S-1°N).

902 Figure 14: Correlations between interannual variations (1979–2014) of ERA5 JJAS LC fraction in NW-
903 Gabon and different atmospheric fields. Top panels: correlation maps for ERA5 (thick white lines: 0.05
904 significance level; thin white lines: -0.6 and 0.6 isocorrelations). Central panels: total correlations
905 between MW-Gabon LC fraction and regional indices computed over the yellow boxes shown on the
906 maps (stars indicate correlations significant at $p < 0.05$, and big stars at $p < 0.01$), for ERA5 and CMIP6
907 coupled simulations. Bottom panels: same as central panels but for partial correlations independently
908 of SST variations southwest of Gabon.

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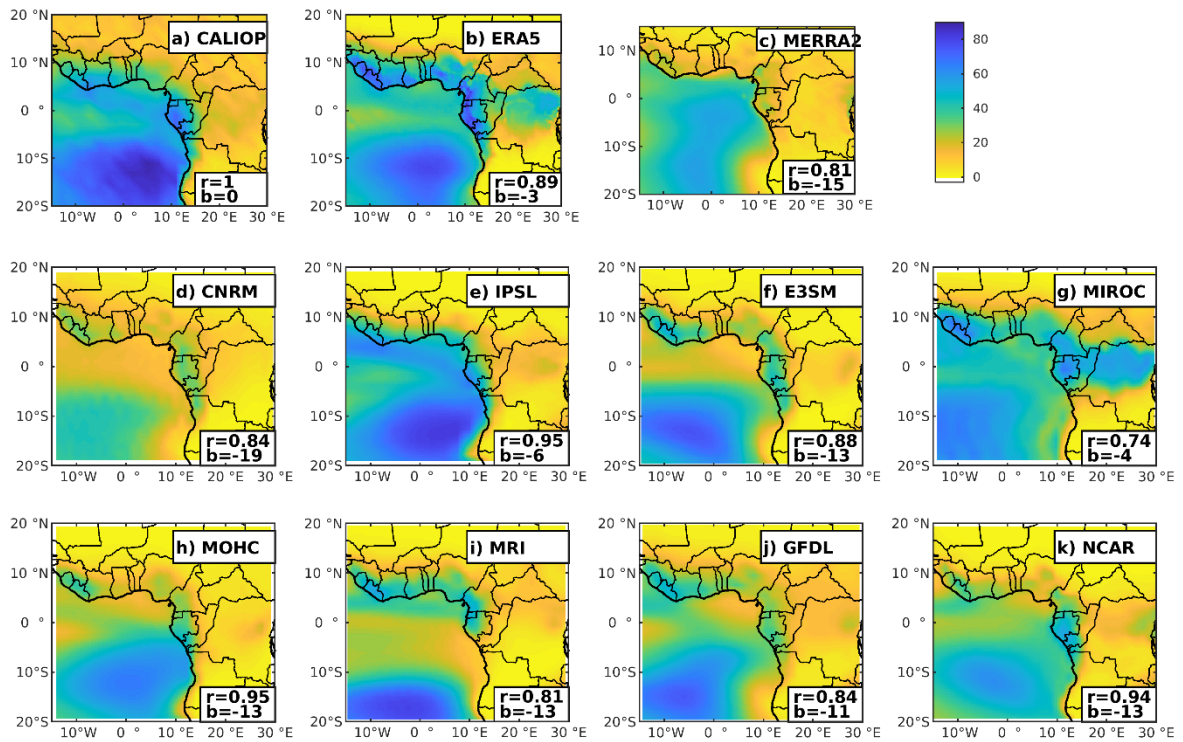


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912 Figure 1: Map of Western Equatorial Africa with the surface stations extracted from the ISD (a) and
913 EECRA (b) databases to compute low cloud statistics. Colour dots: mean JJAS low cloud frequency (a)
914 and low cloud fraction (b), in percentages. Red boxes border the areas for the LCC regional indices.

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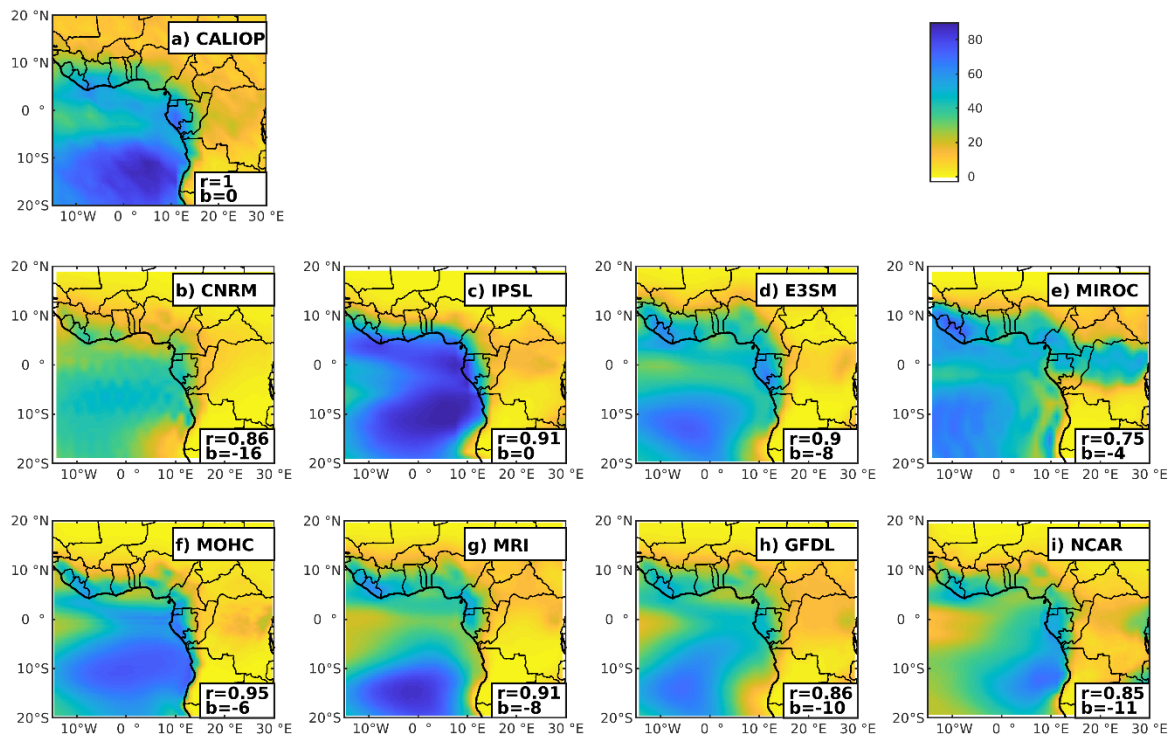
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Figure 2: JJAS mean low cloud fraction (in %) for CALIOP (a), ERA5 (b), MERRA2 (c) and CMIP6 coupled simulations: CNRM (d), IPSL (e), E3SM (f), MIROC (g), MOHC (h), MRI (i), GFDL (j), NCAR (k). Means are computed over the period 1979–2014 (1980–2014 for MERRA2). In the boxes, r is the pattern correlation with CALIOP and b is the mean bias (in % cloud fraction).

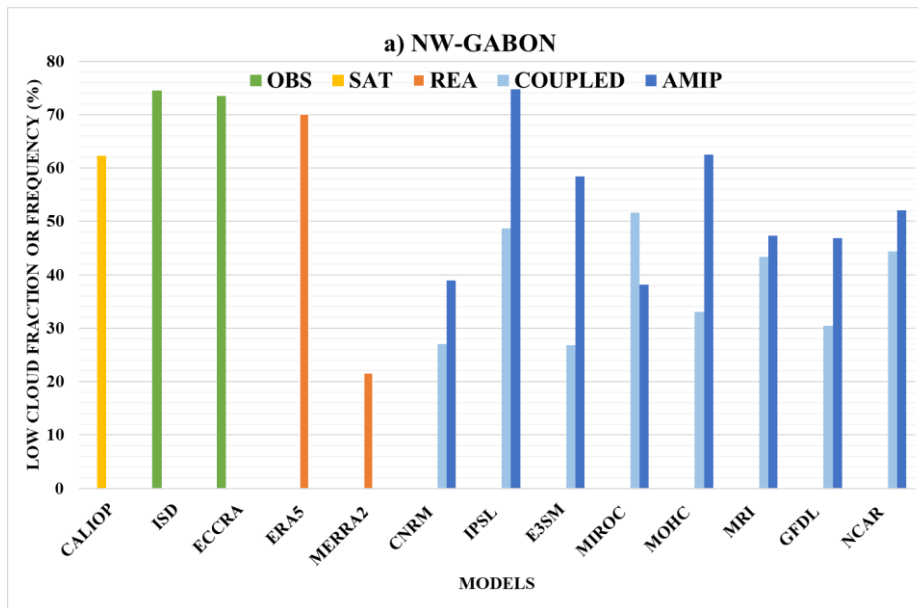


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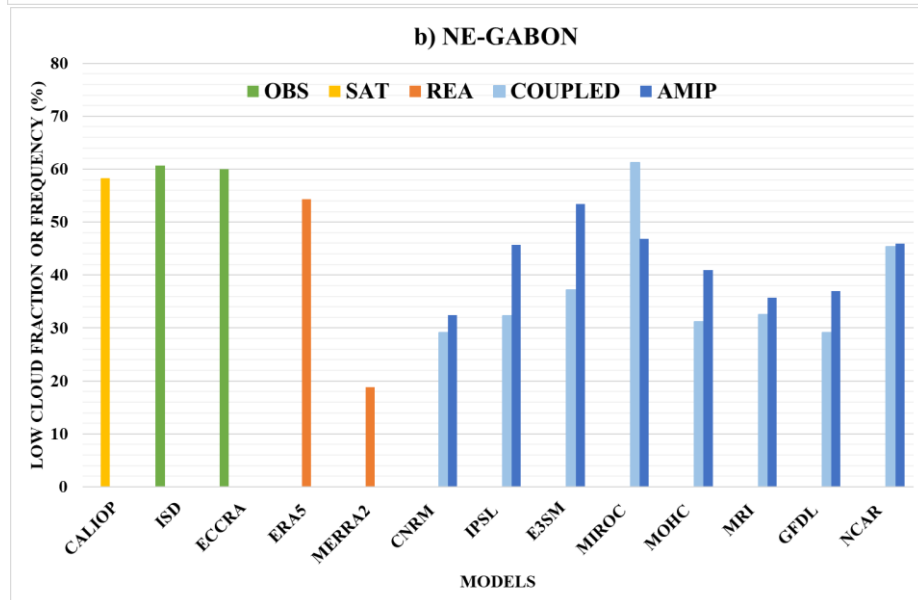
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Figure 3: Same as figure 2 but for CALIOP (a) and CMIP6 atmosphere-only simulations from CNRM (b), IPSL (c), E3SM (d), MIROC (e), MOHC (f), MRI (g), GFDL (h), NCAR (i).



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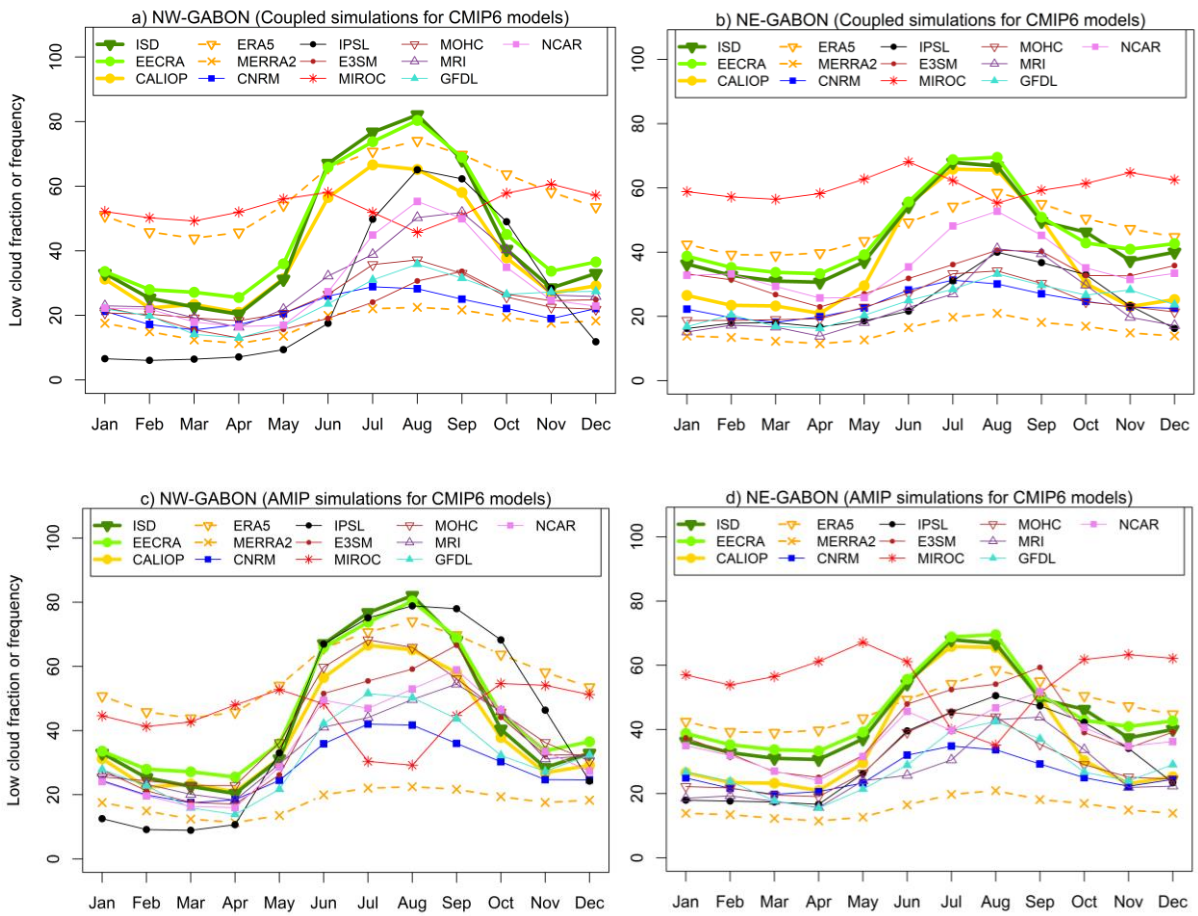
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930 Figure 4: JJAS mean low cloud cover over NW Gabon (a) and NE Gabon (b). See table 1 for the
 931 definition of low cloud cover and the period used for computation in each dataset.

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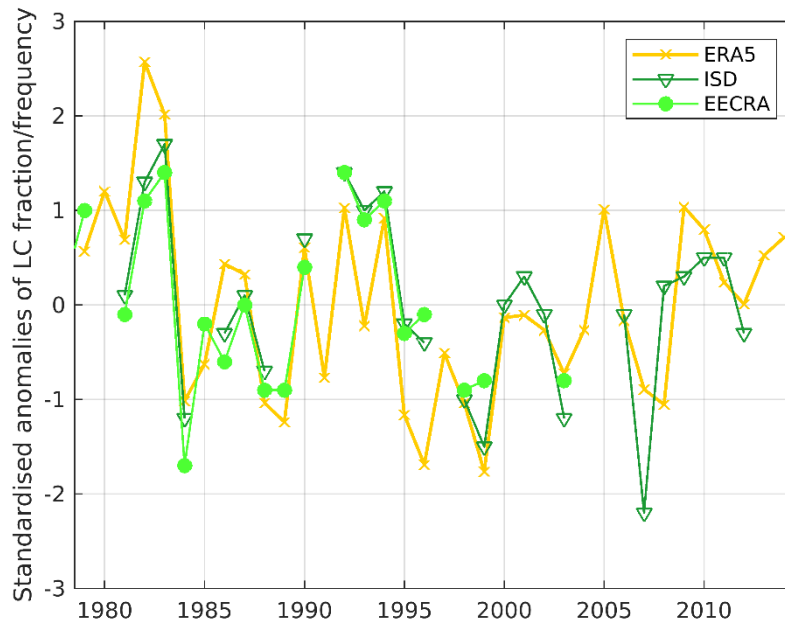
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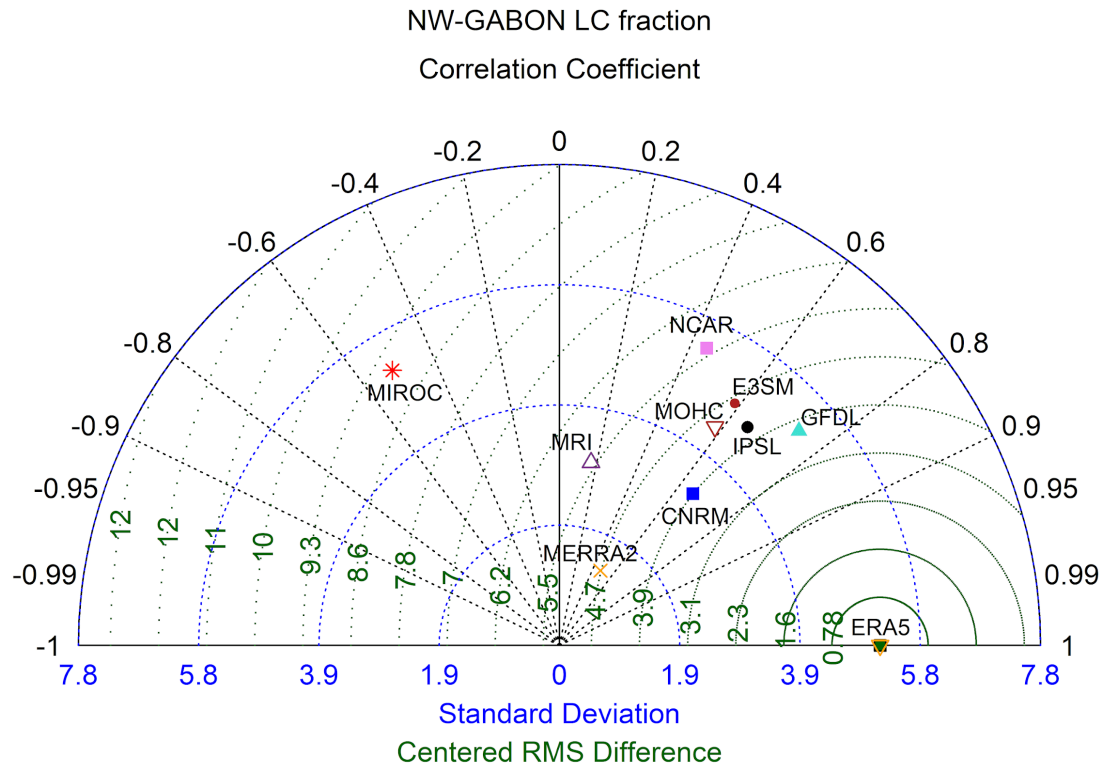
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 942 ERA5 reanalysis (LC fraction) as well as in ISD (LC frequency) and EECRA (LC fraction) observations.

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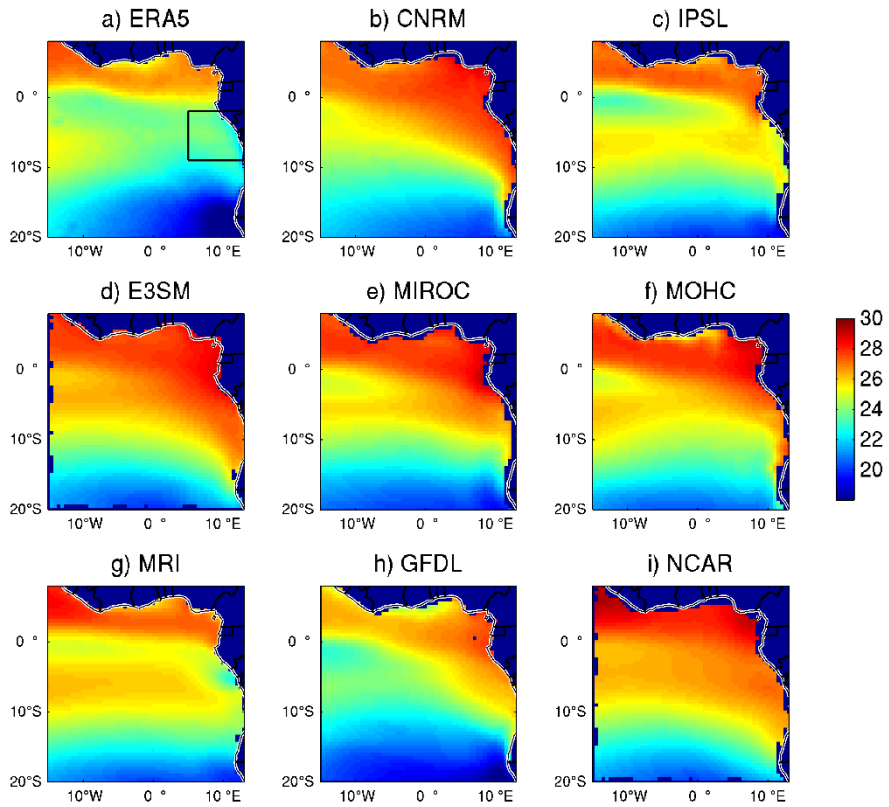
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Figure 7: Taylor diagram of JJAS 1979–2014 NW-Gabon low cloud fraction in MERRA2 and CMIP6 atmosphere-only simulations, with ERA5 as the reference. Black dotted lines: correlation coefficients.

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Blue dotted lines: standard-deviations. Green lines: RMSE.

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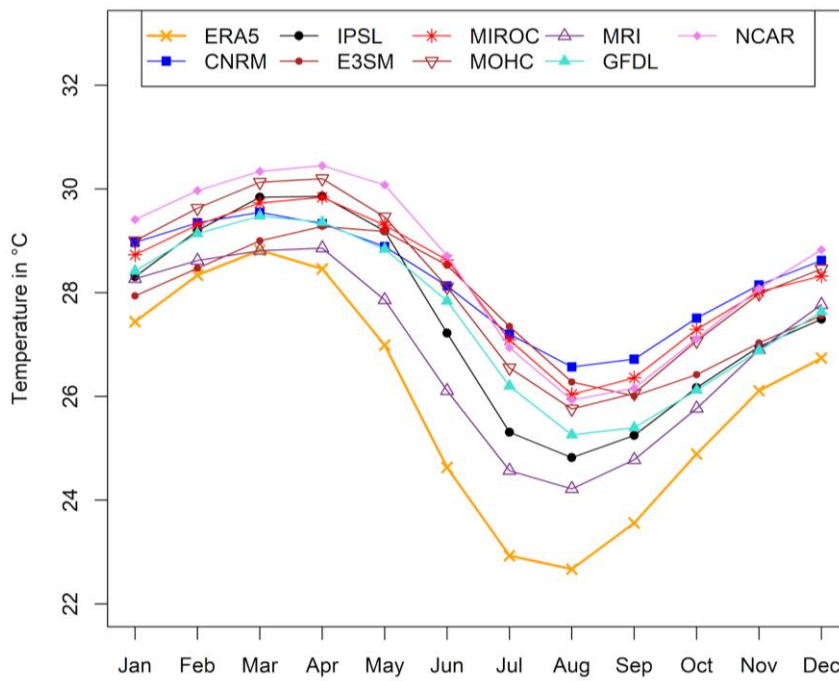
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950 Figure 8 : JJAS mean SST (1979–2014, °C) over the South Atlantic Ocean in ERA5 (a) and CMIP6
 951 coupled simulations: CNRM (b), IPSL (c), E3SM (d), MIROC (e), MOHC (f), MRI (g), GFDL (h), NCAR (i).

952 The location of the Gabon SST index is shown on panel (a).

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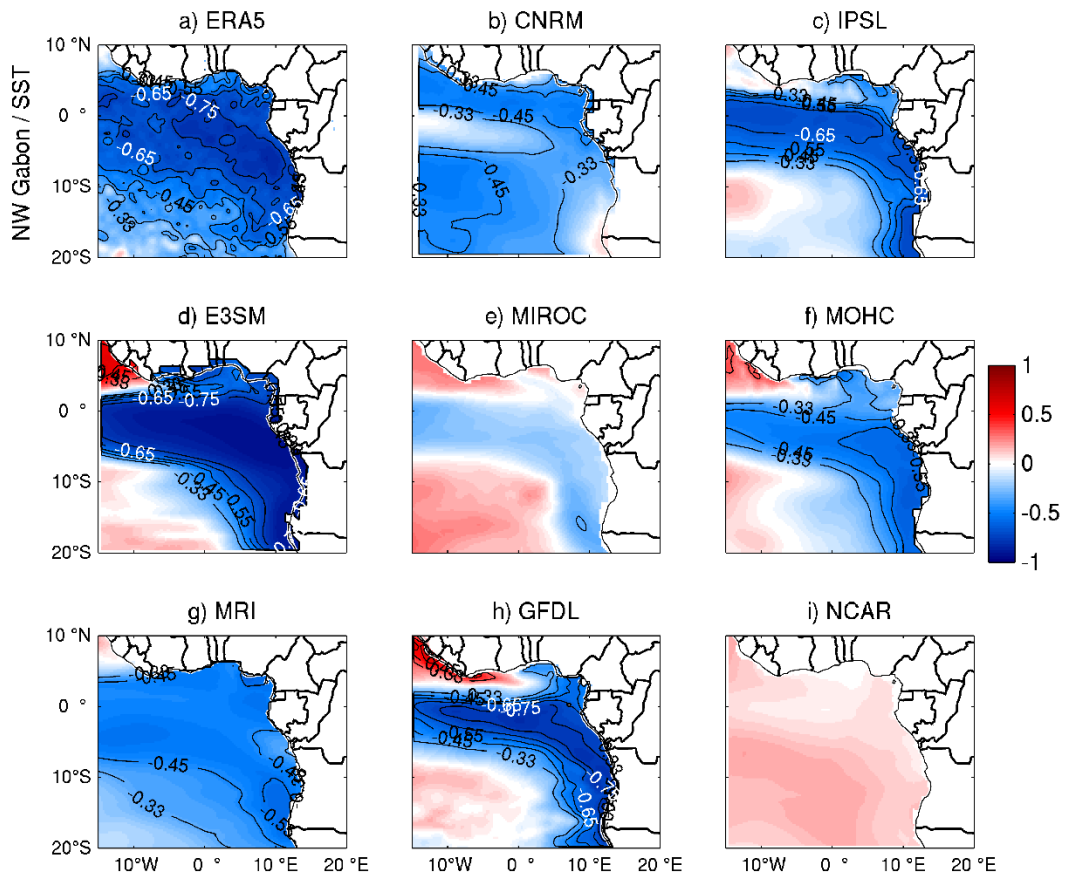
Figure 9 : Mean annual cycle (1979–2014) of SST over the region [9–2°S, 5–13°E] in the Atlantic Ocean southwest of Gabon (boxed area on figure 8a): ERA5 reanalysis and CMIP6 coupled simulations.

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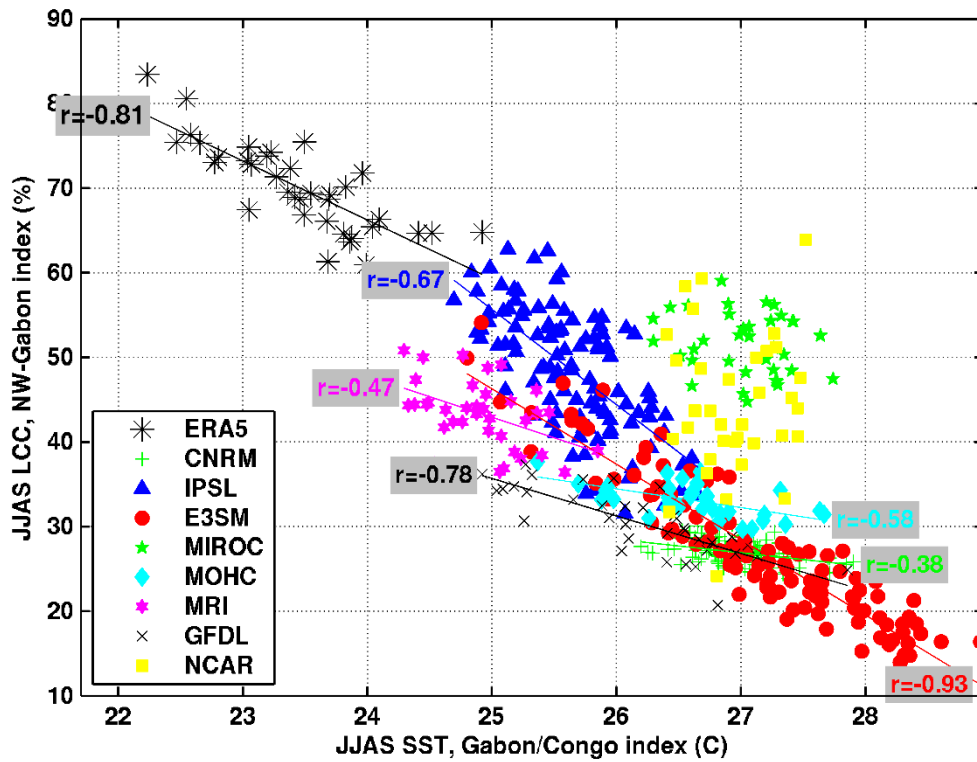
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962 Figure 10: Internal correlations between interannual variations (1979-2014) of JJAS SST and low cloud cover in NW-Gabon, in ERA5 and in each CMIP6 coupled model. Values above 0.33 / below -0.33 are
963 significant at $P < 0.05$.
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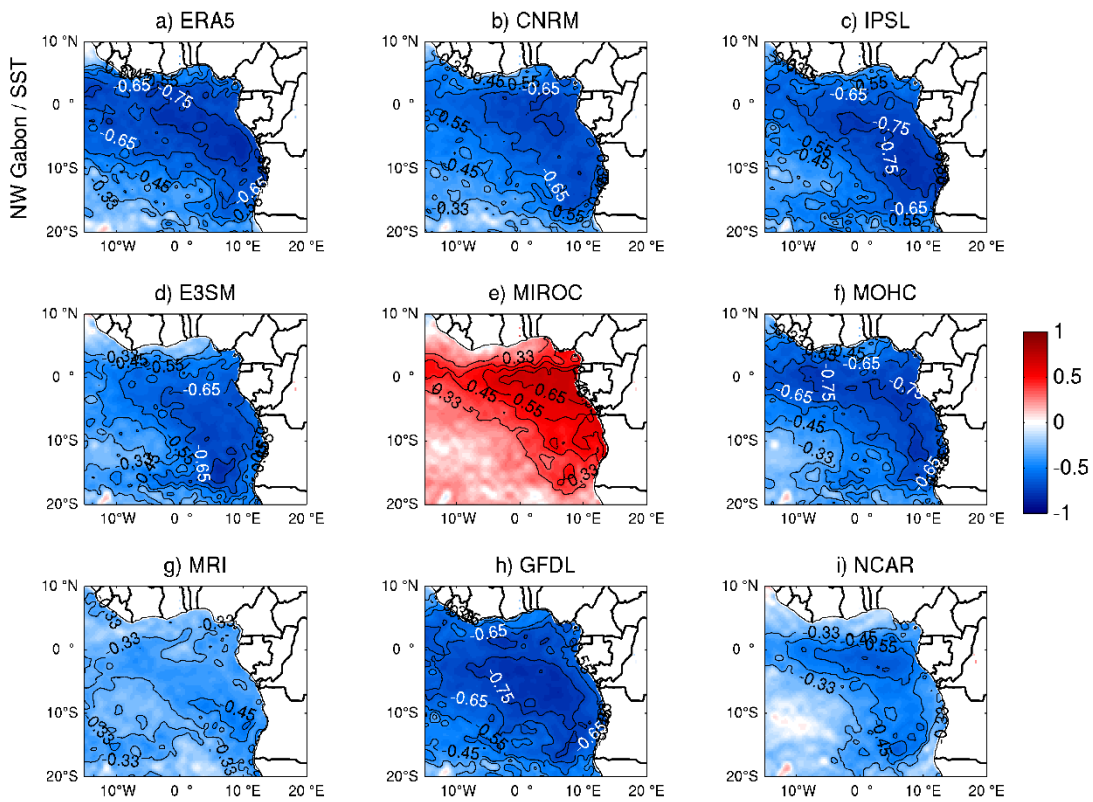


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967 Figure 11: Scatter plot of LC fraction in NW-Gabon versus SST over the Atlantic Ocean southwest of
 968 Gabon [9–2°S, 5–13°E], for ERA5 and for each of the 8 CMIP6 coupled models. Each marker is the
 969 JJAS mean of a given year. Regression lines are shown when the cloud fraction significantly correlates
 970 ($p < 0.05$) with SST.

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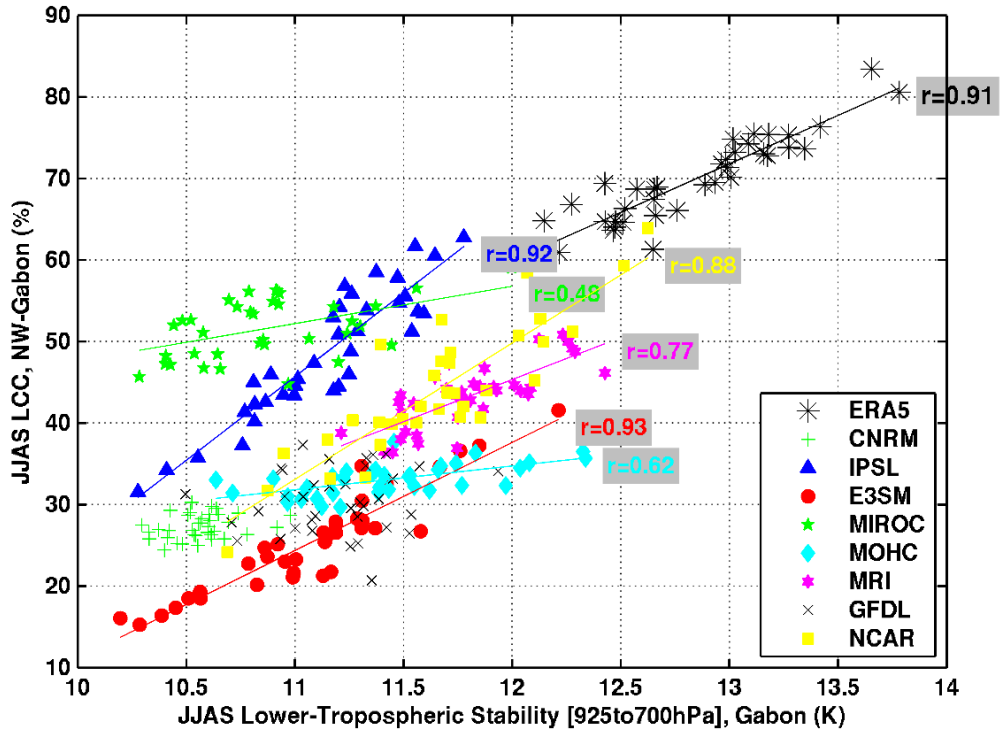
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Figure 12 : Same as figure 10 but for CMIP6 atmosphere-only simulations

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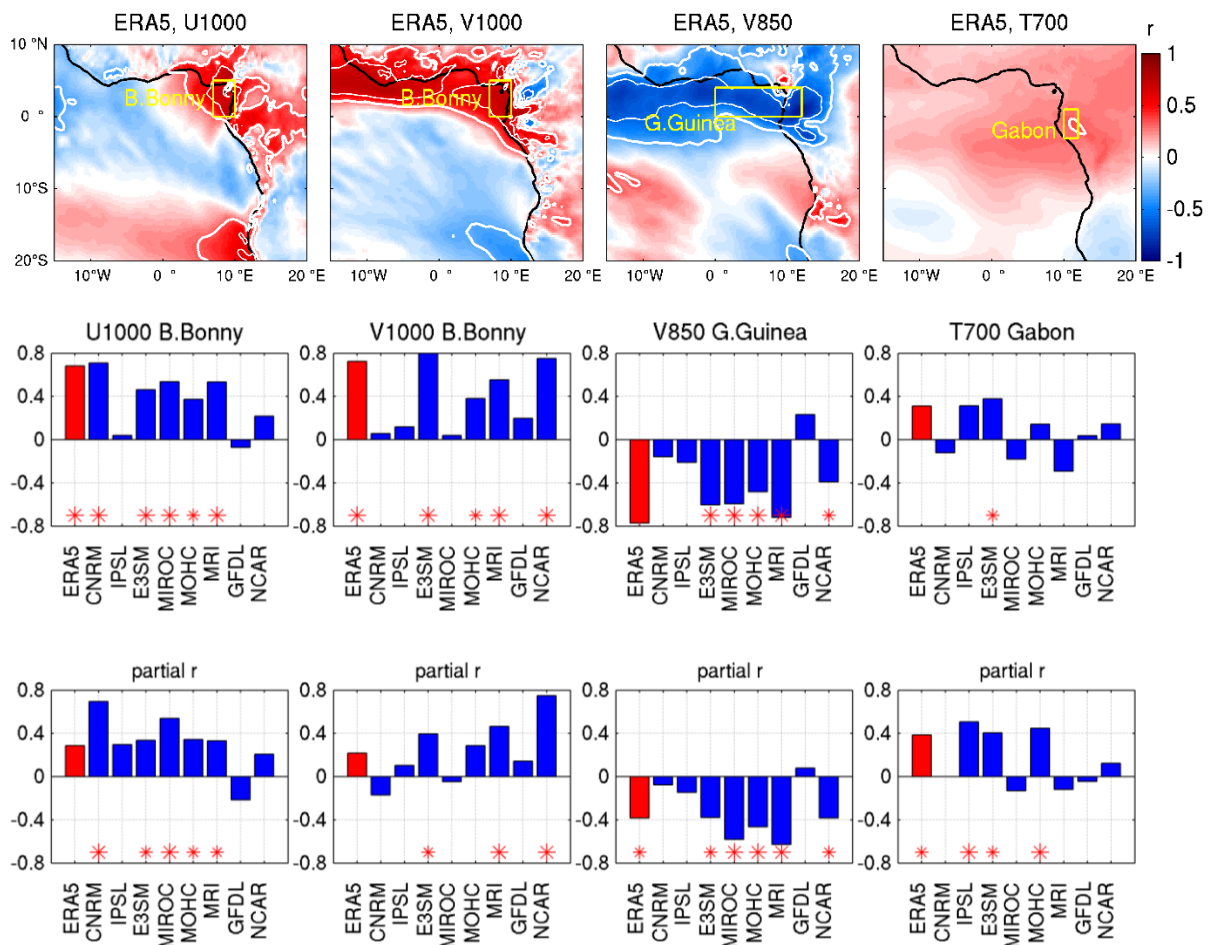
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Figure 13: As in figure 11 but for LC fraction in NW-Gabon versus Lower-Tropospheric Stability (LTS) between 925 and 700 hPa over Gabon (10-12°E, 3°S-1°N).

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986 Figure 14: Correlations between interannual variations (1979–2014) of ERA5 JJAS LC fraction in
 987 NW-Gabon and different atmospheric fields. Top panels: correlation maps for ERA5 (thick white lines:
 988 0.05 significance level; thin white lines: -0.6 and 0.6 isocorrelations). Central panels: total
 989 correlations between MW-Gabon LC fraction and regional indices computed over the yellow boxes
 990 shown on the maps (stars indicate correlations significant at $p < 0.05$, and big stars at $p < 0.01$), for
 991 ERA5 and CMIP6 coupled simulations. Bottom panels: same as central panels but for partial
 992 correlations independently of SST variations southwest of Gabon.

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