Southern African summer-rainfall variability, and its teleconnections, on interannual to interdecadal timescales in CMIP5 models

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1 **Southern African summer-rainfall variability, and its teleconnections, on**

2 **interannual to interdecadal timescales in CMIP5 models**

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Abstract   This study provides the first assessment of CMIP5 model performances in simulating southern Africa (SA) rainfall variability in austral summer (Nov–Feb), and its teleconnections with large-scale climate variability at different timescales. Observed SA rainfall varies at three major timescales: interannual (2–8 years), quasi-decadal (8–13 years; QDV) and interdecadal (15–28 years; IDV). These rainfall fluctuations are, respectively, associated with El Niño Southern Oscillation (ENSO), the Interdecadal Pacific Oscillation (IPO) and the Pacific Decadal Oscillation (PDO), interacting with climate anomalies in the South Atlantic and South Indian Ocean. CMIP5 models produce their own variability, but perform better in simulating interannual rainfall variability, while QDV and IDV are largely underestimated. These limitations can be partly explained by spatial shifts in core regions of SA rainfall variability in the models. Most models reproduce the impact of La Niña on rainfall at the interannual scale in SA, in spite of limitations in the representation of ENSO. Realistic links between negative IPO are found in some models at the QDV scale, but very poor performances are found at the IDV scale. Strong limitations, *i.e.* loss or reversal of these teleconnections, are also noted in some simulations. Such model errors, however, do not systematically impact the skill of simulated rainfall variability. This is because biased SST variability in the South Atlantic and South Indian Oceans strongly impact model skills by modulating the impact of Pacific modes of variability. Using probabilistic multi-scale clustering, model uncertainties in SST variability are primarily driven by differences from one model to another, or comparable models (sharing similar physics), at the global scale. At the regional scale, *i.e.* SA rainfall variability and associated teleconnections, while differences in model physics remain a large source of uncertainty, the contribution of internal climate variability is increasing. This is particularly true at the QDV and IDV scales, where the individual simulations from the same model tend to differentiate, and the sampling error increase.

1. Introduction

Southern Africa (SA, south of 20°S) is known to be particularly vulnerable to climate change due to a combination of a naturally high degree of climate variability and high reliance on climate-sensitive activities, such as rain-fed agriculture (Conway et al. 2015). In particular, during the main rainy season, *i.e.* austral summer (Nov–Feb, NDJF), SA rainfall has been shown to vary over ranges of timescales from synoptic (3–7 days; *e.g.* Todd and Washington 1999; Hart et al. 2012; Macron et al. 2014) to decadal ($\geq$ 10 years; *e.g.* Dyer and Tyson 1977; Tyson 1981 1986; Mason and Jury 1997, Dieppois et al. 2016), as well as potential complex interactions across timescales. For instance, Cook (2001) and Ratnam et al. (2014) proposed that El Niño Southern Oscillation (ENSO) generates atmospheric Rossby waves in the Southern Hemisphere, which could be responsible for longitudinal shifts of the South Indian Convergence Zone (SICZ), where synoptic-scale rain bearing systems that affect southern Africa, such as tropical-temperate troughs (TTTs), preferentially develop (Todd and Washington 1999; Hart et al. 2012; Macron et al. 2014). Similarly, Dieppois et al. (2016) and Pohl et al. (2018), highlighted that part of the non-linearity in the relationship between ENSO and summer SA rainfall, which is prominent at the interannual timescale, could be explained by interactions with the Interdecadal Pacific Oscillation (IPO) and the Pacific Decadal Oscillation (PDO) at the quasi-decadal (8–13 years; QDV) and interdecadal (15–28 years; IDV) timescales, respectively. These studies also suggested that ENSO-like shifts and modulations of the Walker circulation in response to the IPO and PDO are interacting with regional ocean-atmospheric circulations, such as the South Indian Ocean Dipole (Morioka et al. 2015), leading

76   to shifts in the SICZ and modulations of the TTT occurrence. However, despite the importance

77   of these decadal timescales in SA rainfall variability, and their impact on societies, little has

78   been done to examine the ability of global climate models, particularly those that constitute the

79   Coupled Model Intercomparison Project-phase 5 (CMIP5), to reproduce such processes on

80   interannual to interdecadal timescales.

81

82   Model-based studies in southern Africa have highlighted large differences between climate

83   models, especially in their estimates of historical rainfall (Hewitson and Crane 2006; Nikulin

84   et al. 2012; Kalogomou et al. 2013; Dieppois et al. 2015; Munday and Washington 2016 2018).

85   While models reproduce the annual cycle of rainfall reasonably well, there are large

86   discrepancies in rainfall amount, and in particular in austral summer (*e.g.* Dieppois et al. 2015;

87   Munday and Washington 2016 2018). As illustrated in Fig. 1a-b, most CMIP5 models

88   significantly overestimate summer-rainfall, especially in areas of greater rainfall such as the

89   north-eastern region of southern Africa (where more than 60% of models show an average wet

90   bias of 34 mm.months^{-1} or +41%). However, long-term SA rainfall variability has been poorly

91   studied despite of the extensive use of CMIP5 models for climate impact assessment.

92

93   Some authors have proposed that part of such bias in SA rainfall could be explained by

94   significant model-dependency on the strength of the Angola Low amongst CMIP5 models

95   (Munday and Washington 2016; Lazenby et al. 2016), but underlying drivers of these model

96   uncertainties remain unclear. Such uncertainties in CMIP5 models could also be explained

97   through misrepresentations of the linkage between regional circulation and large-scale modes

98   of climate variability. This is, for instance, the case for ENSO (Dieppois et al. 2015), which has

99   major influences on SA rainfall variability (*e.g.* Ropelewski and Halpert 1987 1989; Lindesay

100 1988; Mason and Jury 1997; Rouault and Richard 2005; Kane 2009; Crétat et al. 2012; Ratnam

et al. 2014; Hoell et al. 2015; Dieppois et al. 2016). Dieppois et al. (2015) thus pointed out that anomalous westward extensions of ENSO patterns in the CMIP5 models were leading to wet biases in SA during El Niño events, as a response to anomalously continental locations of the SICZ. This is consistent with recent findings from James et al. (2018), who identify too many TTTs, and too much rainfall from TTTs in HadGEM3-GC2. Similarly, decadal ENSO-like patterns related to the IPO and PDO, and their interactions with atmospheric regional circulations, which also play an important role in SA rainfall variability (Dieppois et al. 2016; Malherbe et al. 2016; Pohl et al. 2018), could potentially contribute to CMIP5 model uncertainties over the region. Decadal rainfall anomalies have, for instance, been shown to explain a large part of the persistent drought in this region between the 1960s and 1990s (*e.g.* Richard et al. 2001; Rouault and Richard 2005; Dieppois et al. 2016; Malherbe et al. 2016; Pohl et al. 2018).

At the global scale, decadal rainfall variance has been shown to be largely underestimated in the CMIP3 and CMIP5 models (Ault et al. 2012). Decadal sea-surface temperature (SST) variability is often underestimated in the Pacific (Ault et al. 2013; Laepple and Huybers 2014; Henley et al. 2017; Power et al. 2017) and overestimated in the North Atlantic (Ba et al. 2014; Menary et al. 2015). This suggests that future climate projections could poorly represent decadal variability, and offer a limited view of prolonged drought and hydro-meteorological risks. Underlying drivers of such model uncertainties however remain unclear, especially at these timescales, and might be region-dependent (Hawkins and Sutton 2009; Deser et al. 2012). So far, no study has attempted to address these issues in SA. Using a time-space approach based on spectral analysis and a probabilistic clustering, this study then aims to: i) identify potential key sources of uncertainties in the CMIP5 models at different timescales; ii) discuss the respective contributions of different model physics and internal climate variability to the

126   CMIP5 model uncertainties at those timescales; iii) better understand processes driving SA

127   rainfall variability, especially using CMIP5 multimodel ensemble.

128

129   This paper is organized as follows. In section 2, the datasets and methods are described. In

130   section 3, we analyse the ability of CMIP5 models to simulate observed timescales of summer

131   SA rainfall variability. In section 4, we assess model skill to simulate global SST variability at

132   decadal timescales, and the teleconnections between SA rainfall and global SST. In section 5,

133   we discuss the potential uncertainties related to the sample sizes (*i.e.* length and number of

134   simulations per model), and the capability of each model, using longer-term model simulations.

135   We then show in section 6 how four contrasting CMIP5 models represent atmospheric bridges

136   linking the Pacific Ocean and SA. Finally, our main results are interpreted and discussed in

137   section 7.

138

139   **2. Data & Methods**

140   *2.1. Observations*

141   The Climatic Research Unit (CRU) dataset is used to compare observed and simulated summer

142   SA rainfall variability (Harris et al. 2014; Table 1). The summer-rain region, which is here

143   defined as the region where the wettest months occur in NDJF, extends to all the north-eastern

144   part of southern Africa (Fig. 1c). To optimally investigate summer-rainfall variability and its

145   teleconnections, a summer-rainfall index (SRI) has been constructed by averaging the values

146   over the summer region, as displayed in Fig. 1c. According to Dieppois et al. (2016), the quality

147   of the SRI is quite stable throughout the 20th century, as a satisfactory number of rain gauges

148   was always available over the region. In addition, very similar results were found using Global

149   Precipitation Climatology Centre full data reanalysis version 7.0 (Schneider et al. 2014).

150

151 To examine the summer teleconnections with global SSTs, we used the extended reconstructed

152 SST version 4 (ERSST.v4) of the National Climatic Data Centre (Huang et al. 2015; Table 1).

153 Version 4 does not use satellite data, and is thus coherent over the whole time period. It is not

154 affected by the cold SST bias induced by the use of satellite observations at the end of the 20th

155 century (Reynolds et al. 2002). Uncertainty related to the choice of the observed SST datasets

156 has been assessed in Dieppois et al. (2016), who compared the composite SST anomalies

157 associated with SA rainfall from ERSST.v4 to those obtained using the HadISST1 (Rayner et

158 al. 2003) and COBE SST2 (Hirahara et al. 2014) datasets: an agreement greater than 90%

159 between datasets was found regardless the timescale, ensuring the reliability of our reference

160 SST dataset.

161

162 As recommended in Zhang et al. (2013), the 20th Century Reanalysis version 2c (20CR.v2c;

163 Compo et al. 2006 2011) is used as reference to discuss the representation of atmospheric

164 bridges between the Pacific Ocean and SA (Table 1). Such atmospheric bridges are here

165 depicted through velocity potential (φ) and stream function (ψ) composite anomalies in the

166 lower and upper troposphere (850–600 and 400–150 hPa). The 20CR.v2c assimilates only

167 surface pressure, and uses monthly SST and sea ice distributions as boundary conditions. Such

168 a modelling and data assimilation strategy that remains constant over the entire time period

169 allows spectral decompositions in analysing atmospheric circulation across different timescales

170 with a reduced sensitivity to time-varying availability of observational datasets. The density of

171 the observational network, *e.g.* amounts of assimilated data, as well as the quality of the SST

172 field used as boundary conditions, remains nevertheless an intractable problem. This is likely

173 to reduce the quality of the reanalyses, and the consistency between its different members, for

174 the first decades of the period (Pohl et al. 2018). However, atmospheric composite anomalies

175 associated with SA rainfall from all reanalysis members were consistent and significantly

176 correlated with the ensemble mean, suggestive of weak inter-member uncertainty (Dieppois et

177 al. 2016).

178

179 ***2.2. CMIP5 model output***

180 Performances have been assessed against observations using historical runs from 28 CMIP5

181 models (Table 1), which simulate climate variability from the mid-19th century to the early 21st

182 centuries, and are driven by observed estimate of anthropogenic and natural forcings (Taylor et

183 al. 2012). Initialization schemes are model dependent. Models from the same institutions or

184 different institutions can share (successive) versions of the same atmospheric, oceanic, land

185 surface and sea-ice components, and, therefore use very similar physics for simulating some

186 parameterized processes of the climate system (Table 2). The spatial resolutions also change

187 from one model to another (Table 1). The ocean grids were interpolated on orthogonal

188 curvilinear grid in some models, making comparison difficult with regular grids, and have thus

189 been remapped on a regular $2° \times 2°$ resolution grid using bilinear interpolation.

190

191 To assess the contribution of internal climate variability, all calculations have been performed

192 on each individual member, giving a total of 95 simulations (Table 1). In addition, to test the

193 uncertainties associated with the sample sizes (*i.e.* length and number of simulations per model),

194 which might be limiting at decadal timescale, longer-term pre-industrial control (piControl)

195 simulations have been used in Section 5 (Table 1).

196

197 Model-simulated SRI has been calculated by averaging summer-rainfall amounts spatially in

198 each historical and piControl runs from the 28 CMIP5 models (Fig. 1c). The simulated summer-

199 rainfall region matched well with that observed, although their spatial extension sensibly varies

200 from one model to another (Fig. 1c).

201

2.3. *Timescales of variability and associated teleconnections*

In section 3, we first compare the significant timescales of observed SRI variability with those

simulated in the 95 members from the 28 selected CMIP5 models using fast Fourier transform

(FFT). Significance tests of the FFT spectrum assumes a red-noise background spectrum for

the null hypothesis, which is tested by 10,000 Monte Carlo simulations of first-order

autoregressive (AR[1]) processes (Ghil et al. 2002). We next compare the SRI variance

according to the three dominant timescales identified in observations (*i.e.* interannual: 2–8 year;

QDV: 8–13 year; IDV: 15–28 year; Dieppois et al. 2016) by submitting observed and simulated

time series to FFT band-pass filtering. To reduce trend effects (Wu et al. 2007), the SRI indices

are preliminary detrended using a locally weighted linear regression, with span equal to the

length of the data. We then compute the centered ratio of standard deviation (*rSD*), here

expressed as a percentage:

$$centered.rSD = 1 - \frac{sd\left(SRI[obs]^{\,t}\right)}{sd\left(SRI[sim]^{\,t}\right)} \times 100 \quad (1)$$

where *sd* refers to the standard deviations of the time series, and *t* indicates the corresponding

timescales. Statistical significance of equality between observed and simulated variance is

estimated using a two-sided Fisher's *F* test at $p = 0.05$. The same procedure is then applied to

each grid-point over the SA region, and to global SST in section 4.

219

In section 4, we also assess the ability of CMIP5 models to simulate teleconnection between

SRI and global SSTs. After replicating the filtering procedure described above to SST datasets,

composite analyses are performed to construct typical states of global SSTs associated with SA

rainfall fluctuations. Two sets of SST anomalies are produced for each timescale, where the

SRI exceeds ± 1 standard deviation (*i.e.* wet and dry anomalies); the resulting composites thus

describe the difference in SST between wet and dry conditions over SA. Statistical significance

226 is estimated by testing the difference in mean between wet and dry SST anomalies using a two-

227 sided Student's *t* test at $p = 0.05$. When time series are serially correlated, the degrees of

228 freedom are adjusted by recalculating the "effective sample size" (N^{eff}). This is given by the

229 following approximation (Yue and Wang 2004):

230 $$\frac{N}{N^{eff}} = 1 + \frac{2}{N(N-1)(N-2)}\sum_{i=1}^{t}(N-i-1)(N-i-2)ts(i) \qquad (2)$$

231 where *N* is the number of observations in the sample, *ts(i)* is the serial correlation between ranks

232 of the observations for lag *i*, and *t* is the maximum time lag considered. This procedure has then

233 been replicated for piControl simulations in section 5, and to examine the performance of the

234 models to reproduce atmospheric bridges between the Pacific basin and SA in section 6. Note

235 that, while the present study aims at identifying climate processes associated with different

236 ranges of SA rainfall fluctuations, some non-linearity between SST anomalies associated with

237 wet and dry years only emerge at the interannual timescale (Fig. A1).

238

239 **2.4.** *Assessing and narrowing model uncertainties*

240 In sections 3 and 4, model performance is systematically assessed through Taylor diagrams

241 (Taylor et al. 2001). As mentioned in earlier studies (Hawkins and Sutton 2009; Deser et al.

242 2012), at the regional scale, model uncertainties are increasing at decadal timescales due an

243 increasing contributions of internal climate variability, adding to problems in model physics.

244 This enhances diversity in the CMIP5 simulations, as simulations of the same model are likely

245 to drift from one another, making meaningless the use of simple statistics (*e.g.* model mean and

246 spread). Similarly to previous studies (*e.g.* Jun et al. 2008; Knutti et al. 2010 2013), a clustering

247 approach has therefore been used to quantify the similarities between all models, and between

248 simulations of the same model without predefined assumption. The relative contributions of

249 model physics and internal climate variability could thus be discussed by assessing the inter-

250 simulation spread within the CMIP5 framework, while identifying recurrent patterns.

251

The similarities between the 95 simulated spatial patterns of SA rainfall variability, global SST variability and composite SST anomalies (*cf.* sections 2.3-4), have thus been quantified at each timescale using Ward's agglomerative criteria applied to Euclidean distances (Ward 1963; Crétat et al. 2018). In addition, we used a multi-scale bootstrap approach, allowing for estimation of the probability of each cluster (Shimodaira 2002, 2004), to optimize the identification of recurrent and spatially coherent clusters within the multimodel ensemble (Fig. A2). To estimate approximately unbiased probability that a cluster appears in the replicate, 10,000 bootstrap resampling over 33 different spatial lengths of the data (2% to 180% of the spatial domain, *i.e.* 330,000 iterations) are used (Fig. A2). Randomly resampling the spatial domain with different sizes thus enables to reduce the uncertainty associated with the selected grid-resolution, and to balance the weight of different regions (*e.g.* Pacific vs. Atlantic). Only clusters showing $p \geq 0.90$ have been considered as robust (Fig. A2). Clusters have been named as #CL1[pr]- to n[pr]-int for rainfall variability at the interannual timescale, and as #CL1[pr] to n[pr]-QDV and IDV at the QDV and IDV timescales (abbreviation [sstvar] and [sstano] have been used for clusters of global SST variance and composite anomalies, respectively).

267

In addition, in section 5, we discussed the sampling uncertainties in simulating observed statistics using historical and the longer-term piControl runs. The capability to significantly simulate observed SRI variance and global SST teleconnections at the three different timescales has been calculated by replicating the procedure described in section 2.3 for every 113 year time-period through the course of historical and piControl runs. The Fisher F test of equal variance at $p = 0.05$ and Pearson's spatial correlation have been used to quantify the capability to simulate rainfall variance and SST teleconnection, respectively.

275

3. Summer SA rainfall variability

3.1. SRI variability

The ability of CMIP5 models to simulate SRI variability (including its timescales and variance) is displayed in Fig. 2. Corroborating Dieppois et al. (2016), observed SRI exhibits three significant timescales of variability over the 20th century (Fig. 2a): interannual (2–8 years), QDV (8–13 years) and IDV (15–28 years). Simulated and observed FFT spectra strongly differ (Fig. 2a). There are also large differences between FFT spectra from different models, and between simulations from the same model (Fig. 2a), indicating that CMIP5 simulations tend to produce their own variability.

However, as illustrated in Fig. A3, most models, and almost all institutions, can produce significant variability within the interannual, QDV and IDV timescales, suggesting that differences in simulated FFT spectra mostly result from internal climate variability, different resolutions and physics. The ratios of standard deviation between CMIP5 models and observation have thus been calculated at the three different timescales (Fig. 2b). CMIP5 models, perform better in simulating SRI variability at the interannual timescale (-6% average bias) than at the QDV and IDV timescales (-15 and -37% average bias; Fig. 2b). At the interannual timescale, more than 50% of the simulations show similar variance to observations (Fig. 2b), while significant underestimations and overestimations are detected in 35 and 14% of model simulations, respectively (Fig. 2b). At the QDV and IDV timescales, only about 30 and 14% of the CMIP5 simulations, respectively, show significant variance close to observation (Fig. 2b). These simulations always correspond to models producing realistic rainfall variance at the interannual timescale (Fig. 2b), suggesting cross-linkages between timescales in the model errors. Biases in simulating SRI variance are indeed proportionally stronger from the interannual to IDV timescales, especially for model simulations

301   underestimating SRI interannual variability (box plots on Fig. 2b). 51 and 77% of model

302   simulations thus significantly underestimate SRI QDV and IDV, respectively (Fig. 2b).

303

304   ### 3.2. Core regions of summer SA rainfall variability

305   #### 3.2.1. Observations

306   Observed interannual rainfall variability explains approximately 70% of the total variance on

307   average over SA (Fig. 3a). As for the raw data, interannual rainfall variability is clearly more

308   pronounced in the northern and eastern regions (Fig. 3a), where summer-rainfall amounts are

309   greater (Fig. 1a). At the QDV and IDV scales, which both can express more than 10% of the

310   total variance over SA, similar patterns of rainfall variability are identified (Fig. 3a). The QDV

311   is more pronounced on the eastern coastal regions of South Africa, but does not contribute much

312   to total rainfall variability northeast of the central plateau (SA highlands; Fig. 3a), while the

313   IDV is more pronounced in this region (Fig. 3a). In addition, according to earlier studies (Tyson

314   1981 1986; Mason and Jury 1997; Dieppois et al. 2016; Malherbe et al. 2016), the QDV can

315   explain up to 26% of the total rainfall variance over the southwestern regions (Fig. 3a).

316

317   #### 3.2.2. Model performances

318   CMIP5 models show good skills in simulating spatial patterns of summer SA rainfall

319   variability at the interannual timescale (Fig. 4a). Spatial correlations between CMIP5

320   simulations and observation often exceed 0.7 (up to ≥ 0.9), while the normalized mean bias is

321   lower than 1 (Fig. 4a). Model skills remain moderately good at the QDV and IDV timescales

322   ($0.5 \leq r \leq 0.85$), although these scores substantially drop in some simulations at the IDV scale

323   (approaching 0; Fig. 4c). Although some models substantially overestimate spatial variability

324   at each timescale, simulated patterns of rainfall variability are often close to the observed one,

325   suggesting similar patterns than in observation (Fig 4a-c).

3.2.3.   CMIP5 model diversity

328 Multi-scale bootstrapped clustering has been used to identify the recurrent and spatially

329 coherent patterns in simulating summer SA rainfall variability within the CMIP5 multimodel

330 ensemble. While 13 significant clusters are identified at the interannual scale, model diversity

331 substantially increases at the QDV and IDV timescales with 28 and 21 significant clusters,

332 respectively (Fig. 4d).

333

334 At the interannual timescale, clusters primarily refer to the different models and institutions

335 (Fig. 4d). Different parameterizations of the LMDZ atmospheric model however lead to

336 differentiations of the distinct versions of the IPSL model (Fig. 4d). Similarly, CMCC-CESM,

337 which includes carbon cycle feedbacks, differs from other CMCC models (Fig. 4d). Models

338 from different institutions sharing the same atmospheric model (or different versions; Table 2)

339 also tend to be clustered together at the interannual timescale (*e.g.* ACCESS1-0 and MOHC,

340 CMCC-CESM and MPI, or CESM1-BCG and CCSM4; Fig. 4d). In addition, some models

341 from different institutions (*e.g.* ACCESS1-3, CSIRO-Mk3-6-0 and MIROC5), are also

342 regrouped (Fig. 4d). Although the similarities between these models could not be explain here

343 through similarities in model physics, all these models are found to overestimate interannual

344 SRI variability (Fig. 2).

345

346 At the QDV and IDV scales, individual simulations from the same or comparable models,

347 gradually differentiate, increasing cluster diversity (Fig. 4d). For instance, four significant

348 clusters emerge from CNRM-CM5 at the QDV scale, and this is also the case for most models

349 (Fig. 4d). ACCESS1-3, CSIRO-Mk3-6-0 and MIROC5, which all overestimate interannual SRI

350 variability, still have some simulations clustered together at the QDV and IDV timescales (Fig.

351 4d). This differentiation between simulations of the same models suggests larger contributions

352 of internal climate variability to model biases. The different clusters could also still partly

353 discriminate different model physics. This is confirmed in Fig. A4, as correlations between

354 simulations from the same models decrease from interannual to IDV timescales, but remain

355 stronger than correlations between different models.

356

357 *3.2.4. Simulated spatial patterns of SA rainfall variability*

358 Such diversity of simulated SA rainfall variability at the three different timescales is illustrated

359 in Fig. 5. For clarity, names of model simulations describing each clusters are provided in Fig.

360 A5.

361

362 According to observation, CMIP5 models generally simulate greater variability in the NE than

363 in the SW regions regardless of the timescale (Fig. 5). However, slight misrepresentations of

364 core regions of SA rainfall variability help explaining biases detected in SRI variability at all

365 timescales. CMIP5 simulations overestimating SRI variability (#CL1[pr]-int, #CL1-2[pr]-

366 QDV, #CL1, 6[pr]-IDV; Fig. A5) show very realistic patterns, but overestimate rainfall

367 fluctuations in the north-west of the summer-rain region (Fig. 5a-c). In NASA-GISS models

368 (#CL13[pr]-int, #CL5[pr]-QDV, #CL12[pr]-IDV; Fig. A5), rainfall variability is strongest in

369 the eastern coastal regions of SA at all timescales, hence large underestimations further inland

370 (Fig. 5a). At the interannual and QDV scales, MPI models and CMCC models (#CL10[pr]-int

371 and #CL25[pr]-QDV; Fig. A5) simulate too strong rainfall variability in the western region,

372 and underestimate it further east (Fig. 5a). Interestingly, the best performing simulations of SRI

373 variability (#CL2, 6, 7, 10[pr]-int, #CL21, 24[pr]-QDV; Fig. A5) also show significant biases

374 in rainfall variability over SA (Fig. 5a).

375

376   In summary, although the NE-SW gradient in SA rainfall variability is generally well

377   reproduced for all timescales, slight shifts in core regions of SA rainfall variability could

378   explain part of the biases in simulating SRI variability. This leads to great model diversity,

379   suggesting contrasted links with large-scale and/or regional circulation patterns in CMIP5.

380

381 **4. Interannual to interdecadal global SST variability and teleconnections with SA**

382   **rainfall**

383 We examine here the ability of CMIP5 models to simulate global modes of SST variability at

384 these timescales, and their teleconnections with SA rainfall.

385

386   *4.1. Observations*

387 In observations, ENSO is the dominant mode of global SST variability at the interannual

388 timescale (Mann and Park 1994; Klein et al 1999; Ghil et al. 2002; Sarachick and Cane 2010;

389 De Viron et al. 2013), hence significant fluctuations in the equatorial Pacific at $p = 0.05$ (Fig.

390 3b). Positive SRI anomalies are thus primarily related to La Niña events, which are associated

391 with cooler tropical Indian Ocean SSTs (Fig. 3c). Observed interannual SRI variability is also

392 related to the South-West Indian Ocean SST dipole (Reason 1998; Reason and Mulenga 1999;

393 Reason 2001; Behera and Yamagata 2001; Washington and Preston 2006; Hoell et al. 2017,

394 2018), the South Atlantic SST dipole (Fauchereau et al. 2003; Hermes and Reason 2005;

395 Vigaud et al. 2009), and SST fluctuations reminiscent of Benguela Niños/Niñas (Lubbecke et

396 al. 2010; Rouault 2012; Reason and Smart 2015).

397

398 The pattern of SST variability at the QDV timescale is similar to that of ENSO (Tourre et al.

399 1999 2001 2005; Fig. 3b). Wet conditions in SA are once again related to cold anomalies in the

400 east Pacific flanked by a horseshoe pattern of opposite sign, confirming the results by Dieppois

401 et al. (2016). This is consistent with the negative IPO pattern after the definition provided by

402 Power *et al.* (1999), and revisited by Di Lorenzo et al. (2015). This negative IPO occurs

403 concomitantly with cold anomalies in the tropical Indian Ocean (Fig. 3c), as highlighted in

404 Allan et al. (2003). Dipole SST anomalies in the South Atlantic Ocean and the SW Indian Ocean

405 have also been related to SA rainfall at this timescale, in response to shifts in the atmospheric

406 circulation (Venegas et al. 1996 1997; Dieppois et al. 2016). Climate anomalies in the SW

407 Indian Ocean were however clearer in Jury et al. (2014) and Morioka et al. (2015), using a

408 shorter period and other datasets.

409

410 As shown in Tourre et al. (1999 2001 2005), SST variability is particularly pronounced in the

411 North Pacific at the IDV timescale (Fig. 3b). At this timescale, Pacific SST anomalies

412 associated with SRI fluctuations display a horseshoe pattern, which is reminiscent of the PDO

413 (*e.g.* Mantua et al. 1997; Mantua and Hare 2002; Newman et al. 2016). SRI fluctuations have

414 also been connected to SST anomalies in the South Atlantic and Indian Oceans at the

415 interdecadal timescale (Dieppois et al. 2016; Pohl et al. 2018). We thus note cold anomalies in

416 the tropical Indian and South Atlantic Oceans, and warm anomalies in the extra-tropics (Fig.

417 3c). These regional SST anomalies in the adjacent oceans could be associated with enhanced

418 atmospheric circulation in the Southern Hemisphere (Venegas et al. 1996 1997; Dieppois et al.

419 2016), and to the Southern Annular Mode (SAM; Ciasto et al. 2011; Malherbe et al. 2014 2016).

420

4.2. Model performances

422 The performance of CMIP5 models for simulating spatial patterns of global SST variability at

423 the three different timescales are summarized in Fig. 6a. Their respective skills in simulating

424 global SST anomalies associated with SA rainfall variability are displayed in Fig. 6b. Model

425 performances in simulating global SST variability are reasonably good at the interannual

timescale (spatial correlation comprised between 0.45 and 0.75 against observations). Correlations gradually decrease at the QDV ($0.3 < r < 0.7$) and IDV ($0.1 < r < 0.65$) scales (Fig. 6a-b). For the teleconnections between SA rainfall and global SST (Fig. 6b), most models show correlations greater than 0.4 at the interannual timescale. Correlations are weaker at the QDV scale ($-0.6 < r < 0.7$) and weaker still at the IDV scale ($-0.4 < r < 0.4$; Fig. 6a-b).

Global SST variability can be too strong in CMIP5 models regardless the timescale (Fig. 6a). However, some regions, such as the Arctic and the Southern Ocean, strongly suffer from large uncertainties in observation due to data scarcity (Hirahara 2014; Huang et al. 2016). More specifically for SA rainfall, the teleconnections with global SST show very contrasted skills at all timescales, suggesting large model diversity.

4.3. Model diversity

The number of significant clusters of global patterns of SST variability (14, 13 and 15 from the interannual to IDV) and of global SST anomalies associated with SA rainfall (22, 24, 19) is almost constant regardless the timescale (Fig. 6c). The clusters of global SST variability patterns mostly discriminate resembling models (sharing some components or parameterizations; Table 2), in spite of some exceptions (like the different versions of the IPSL model). The situation is far less clear for global SST–SA rainfall teleconnections, especially at the QDV and IDV scales, where intra-ensemble similarities are as much or more important than inter-model similarities (Fig. A6). At these timescales, all CMIP5 model ensembles produce different clusters of global SST-SA rainfall teleconnections, suggesting major contributions of internal climate variability. For instance, CSIRO-Mk3-6-0 simulations, which were converging at the interannual scale, drift into 6 and 5 different clusters at the QDV and IDV scales (Fig. 6c).

4.4. Simulated global SST variability, and teleconnections with SA rainfall

453 CMIP5 model diversity in simulating global patterns of SST variability and SST-SA rainfall

454 teleconnection is illustrated in Figs. 7 and 8, respectively. For clarity, names of model

455 simulations describing each clusters are provided in Fig. A5.

456

457 At the interannual timescale, ENSO patterns are extending too far west and too tightly confined

458 to the equator (AchutaRao and Sperber 2006; Capotondi et al. 2006, Lin 2007; Guilyardi et al.

459 2009; Fig. 7a), which could substantially impact SA rainfall variability, as suggested in

460 Dieppois et al. (2015). Most models link wet conditions in SA to La Niña SST anomalies in the

461 Pacific, and to cold tropical Indian Ocean (#CL4, 6, 9, 10[sstano]-int; Figs. 8a, A5). However,

462 simulated La Niña SST anomalies extend too far west (*e.g.* #CL4, 6, 9[sstano]-int), and/or are

463 too confined to the equatorial latitudes (#C10, 14[sstano]-int; Fig. 8a). These models also

464 simulate the teleconnections with SA rainfall in the South Atlantic and South Indian Oceans

465 (Fig. 8a), but SST anomalies there are too strong, given the systematic overestimations of SST

466 variability (Fig. 7a). This systematic overestimations of SST variability could be due to

467 limitations in simulating wind-stress in the mid-latitude and subtropical regions, which has been

468 reported too strong by as much as 55% in CMIP3 and CMIP5 (Lee et al. 2013). These biases

469 in the adjacent oceans have major implication for SA rainfall variability. As illustrated in Figure

470 9, even though most simulations (~60%) reproduce the main teleconnection with ENSO at

471 interannual scale, only half of them lead to realistic representation of SA rainfall variability.

472 This is because ENSO-induced large-scale climate anomalies are almost always associated with

473 biased regional climate anomalies over the South Atlantic and South (and Tropical) Indian

474 Oceans (Fig. 9), which can substantially modulate their impact on the continent (Hoell et al.

475 2017).

476

477   In other models (*e.g.* #CL7[sstano]-int.; Fig. A5), SA rainfall variability is not significantly

478   related to ENSO at the interannual scale (Fig. 8a). In these models, interannual SRI variability

479   is primarily linked to the South Indian and South Atlantic Oceans (Fig. 8a), denoting changes

480   in the regional atmospheric circulation, *i.e.* changes in wind-stress modifying sensible and latent

481   heat fluxes (Fauchereau et al. 2003). Such regional changes in SSTs could also be associated

482   with the SAM (Ciasto et al. 2011), whose the component driven by ENSO (including the impact

483   on austral summer-rainfall) is not captured in most CMIP5 models (Lim et al. 2016).

484   Interestingly, although those regional climate anomalies are systematically biased, they can lead

485   to good representation of SA rainfall variability (Fig. 9), suggesting error compensations.

486   Underestimations of ENSO anomalies in austral summer could however be at least partly

487   explained by misrepresentations of the seasonality in ENSO variability in some models (Fig.

488   A7). For instance, ENSO activity is peaking between March and August in IPSL models, and

489   is slightly delayed in ACCESS1-3 (Fig. A7). This is not true for CCSM4 and CESM-BCG,

490   which show realistic seasonal timing in ENSO activity, even though largely overestimated (Fig.

491   A7). In some CCSM4 simulations (#CL8[sstano]-int; Fig. A5), wet conditions occur during El

492   Niño events (Fig. 8a), *i.e.* a reversed-sign association compared to observations.

493

494   At the QDV timescale, tropical SST variability in the central Pacific is far too weak in most

495   CMIP5 models (Fig. 7b), suggesting large underestimations of IPO variability. In addition,

496   according to Henley et al. (2017), CMIP5 models locate IPO variability too far west (#CL1, 2,

497   4, 8 and 12[sstvar]-QDV; Figs. 7b, A5). Some models thus simulate negative IPO anomalies

498   associated with cold anomalies in the tropical Indian Ocean (#CL1, 21, 24[sstano]-QDV; Figs.

499   8b, A5). A skilful representation of the IPO teleconnection is however rarely associated with a

500   good representation of SA rainfall variability (Fig. 9). We also systematically found SST dipole

anomalies in both the South Atlantic and South Indian Oceans (Fig. 8b). Interestingly, although, these climate anomalies in the adjacent oceans are biased in most models, they can lead to good reproduction of SA rainfall variability (Fig. 9). This suggests error compensations at the QDV scale also. Some models simulate weak or even reversed relationships between SA rainfall and Pacific SSTs (Fig. 2b). For instance, in #CL11 [sstano]-QDV (Fig. A5), wet conditions are linked to positive IPO (Fig. 8b).

At the IDV timescale, the PDO variability is systematically confined to the North Pacific in most CMIP5 models (Fig. 7c), while it should extend further in the tropics in response to ENSO forcing (Schneider and Cornuelle 2005). Very few simulations, which are the best performing in simulating SRI variability at this timescale (Fig. 2b), link wet conditions over SA to negative PDO anomalies (#CL1-2[sstano]-IDV; Figs. 8c, 9, A5). These simulations also simulate cold (warm) SST anomalies in the tropical (extra-tropical) Indian and South Atlantic Oceans (Fig. 8c). However, the same simulations tend to link SA rainfall to decadal ENSO-like SST anomalies, reminiscent of negative IPO in the tropical Pacific Ocean (Fig. 8c). Indeed, many simulations overestimate IPO-like variability in the equatorial Pacific at the IDV scale (*e.g.* #CL1, 11[sstvar]-IDV; Figs. 7c, A5). Although this could highlight systematic biases in CMIP5 models (*e.g.* Fleming and Anchukaitis 2016), concomitance between IPO and PDO patterns might arise from internal climate variability. In-phase variability of these low-frequency modes is very rare, and has not been observed at this timescale over the instrumental period (Fig. 3b-c).

5. Sample size uncertainties and model capabilities

With an increasing contribution of internal climate variability, regional model evaluations could be influenced by the sample sizes (*i.e.* length and number of simulations per model). This is

526   particularly true at decadal timescales, where historical runs only capture ~14 and ~7 life cycles

527   of QDV and IDV, hence limiting the chance to match the observed "realisation". In this section,

528   we thus discuss the capability of each model by quantifying the chance to reproduce SRI

529   variance and its global SST teleconnections for every 113 year time-period though the course

530   of all historical runs and using the longer-term piControl simulations (Fig. 10). The number of

531   samples used to quantify the model capabilities is not constant, and should be used as an

532   indicator of robustness (Fig. 10).

533

534   At the interannual timescale, half of the CMIP5 models show very good capability ($> 80\%$) to

535   significantly simulate SRI variance equal to observation in historical and piControl runs (Fig.

536   10a). In addition, model capabilities are most of the time weaker in piControl runs than

537   historical runs (Fig. 10a), suggesting that interannual SA rainfall variability is strongly

538   modulated by internal climate variability in longer runs. The capability to simulate significant

539   similar SRI variance between models and observation progressively decreases at the QDV and

540   IDV timescales (Fig. 9a). At the QDV timescale, ~75 and ~90% of CMIP5 models show

541   moderate to low capability in historical and piControl runs, respectively (Fig. 9a). At the IDV

542   timescale, a third and half of the CMIP5 models show some capability using historical and

543   piControl runs, respectively (Fig. 9a). At the QDV and IDV scales, model capabilities are also

544   generally greater in piControl runs than in historical runs (Fig. 9). This suggests that, at these

545   decadal timescales, better performance could be obtained in many models using longer runs (or

546   large-ensembles, which also account better for internal climate variability).

547

548   More mixed results are identified when analysing simulated teleconnections between SRI and

549   global SST anomalies. At the interannual timescale, 50% and 70% of CMIP5 models show

550   moderate to good capability in historical and piControl runs, respectively (Fig. 9b). Better

551 performance could have thus been found at the interannual scale using longer runs (or large-

552 ensembles). Similar results are found at the QDV timescales, even if very few models show

553 good capabilities. Model capabilities are however insensitive to the sample sizes, and are

554 always null, at the IDV timescale (Fig. 10b).

555

556 Interestingly, capabilities in simulating global SST-SA rainfall teleconnection are always

557 weaker than in SRI variance, which are generally greater at all timescales (Fig. 9a-b). This

558 suggest that misrepresentations of atmospheric bridges between the Pacific and SA, and its links

559 to the regional circulation (cf. Sect. 4.4), remain even through the course of piControl runs, and

560 are very little sensitive to internal climate variability. In this regard, GFDL-CM3 could be

561 considered as a reference in simulating both summer SA rainfall and their teleconnections at

562 the interannual timescale (Fig. 10a-b). Some models, such as CSIRO-Mk3-6-0 and, in

563 particular, MPI-ESM-LR, provide good capabilities to portray consistent interannual to QDV

564 fluctuations in both teleconnections and SRI variability (Fig. 10a-b).

565

566 **6. Atmospheric bridges**

567 *6.1. Observed atmospheric anomalies associated with SRI variability*

568 Observed atmospheric bridges between the Pacific and SA are examined through velocity

569 potential and stream function composite anomalies in the lower and upper troposphere (Fig.

570 11).

571

572 At the interannual timescale, La Niña SST events (which favour wet conditions over SA; Fig.

573 3c), are associated with large-scale lower-layer convergence over the western Pacific, and

574 divergence over the eastern Pacific, and reverse signals in the upper troposphere (Fig. 11). This

575 denotes conditions favourable to large-scale ascending motion over the Maritime Continent and

subsiding motions in the eastern Pacific, which is consistent with a westward shift and intensification of the Walker circulation. According to Hoell et al. (2015), changes in vertical winds and convection over the western Pacific result in tropospheric diabatic heating, which in turn force a Gill-Matsuno response over the Indian Ocean basin and surrounding continents (Fig. 11). The Gill-Matsuno response is materialized in the lower troposphere by significant cyclonic circulation poleward and westward of the anomalous diabatic heating over the Maritime Continent, while anticyclonic circulation is detected in the upper layers (Fig. 11). In the Southern Hemisphere, this initiates a Rossby wave-train between the tropics and SA (Hoskins and Ambrizzi 1993; Cook 2001), thereby evidenced by an anticyclonic ridge (Fig. 11). This contributes to an enhancement of the South Atlantic High. Dieppois et al. (2016) argued that westerlies driven by the South Atlantic High then converge with easterlies from the Indian Ocean, leading to ascending motions and convection in SA (Fig. 11). This pattern also corresponds to a westward shift of the SICZ, favouring wet conditions in SA.

Similar mechanisms are identified at the QDV and IDV scales, where both negative IPO and PDO anomalies are associated with a westward shift and intensification of the Walker-type circulation, as well as a Gill-Matsuno response over the Indian Ocean basin (Fig. 11). However, at the QDV timescale, the resulting Rossby wave-train shows a quasi-meridional propagation, and acts to enhance the South Indian High (Fig. 11). This promotes easterly moisture flux from the Indian Ocean (Dieppois et al. 2016), and convergence with south-easterly fluxes from the Atlantic (Fig. 11), increasing rainfall over SA.

At the interdecadal timescale, atmospheric anomalies are much weaker, consistently with the lower contributions of IDV to SA rainfall variability (Pohl et al. 2018). There, the Rossby wave-train, evidenced by cyclonic circulation over subtropical SA, and anticyclonic circulation

601 further north (Fig. 11), modulates the regional circulation over SA. At the same time, significant

602 changes in the meridional circulations take place in the Southern Hemisphere, discernible as

603 alternating cyclonic and anticyclonic circulations in the extra-tropics (Fig. 11). Dieppois et al.

604 (2016) argued that such anomalies could help to enhance both the South Atlantic and South

605 Indian Highs, and potentially the SAM (Malherbe et al. 2016), which then favours convergence

606 and ascending motions over SA (Fig. 11).

607

608 *6.2. Atmospheric anomalies associated with SRI variability in CMIP5 models*

609 Fig. 12 displays circulation composite anomalies in the lower troposphere as simulated by four

610 CMIP5 models with contrasted performances according to section 5.

611

612 In some models, neither rainfall variability nor their SST teleconnections are adequately

613 simulated (Fig. 10). In GISS-E2-R-CC, for instance, underestimations of La Niña SST

614 anomalies at the interannual timescale lead to a weak response of the atmosphere. Significant,

615 but far too weak, ascending motions are identified over the western Pacific, and subsidence

616 occurs over the eastern Pacific (Fig. 12). This is consistent with a westward shift and

617 intensification of the Walker circulation, but the associated Gill-Matsuno response over the

618 Indian Ocean is far too weak (Fig. 12). At the QDV and IDV scales, none of these circulation

619 anomalies are simulated (Fig. 12). This is due to major difficulties in simulating IPO and PDO

620 variability in the equatorial Pacific (Figs. 8, 9). Large underestimations of ENSO variability,

621 which is a common feature in NASA-GISS models (Fig. A7), leads to underestimate SRI

622 variability.

623

624 In other models, rainfall variability at the interannual and QDV timescales is adequately

625 reproduced, but as a response to different large-scale ocean-atmospheric processes (Fig. 10). In

IPSL-CM5B-LR, for instance, the relationship between SA rainfall and ENSO is reversed, and consists of an eastward shift in the Walker circulation. Southward shifts of the South Atlantic and South Indian Highs are also identified, as well as ascendance over the eastern coast of Africa, potentially associated with warm SST there (Fig. 12). This increases rainfall over SA. At the QDV and IDV scales, none of the observed circulation anomalies are simulated (Fig. 12), due to unrealistic IPO and PDO variability (Figs. 7-8). Rainfall QDV is therefore not directly influenced by the Pacific Ocean, but by anomalously strong cyclonic circulations in the subtropics.

GFDL-CM3 is the best performing model at the interannual timescale (Fig. 10). The westward shift and intensification of the Walker circulation, as well as the Gill-Matsuno response over the Indian Ocean are well simulated (Fig. 12). The intensity and the location of the South Atlantic High, and thus convergence and ascendance over SA (*i.e.* the SICZ activity), fluctuate from one simulation to another (Fig. 12). Similarly, contrasting performances are obtained over the Pacific Ocean at the QDV and IDV timescales (Fig. 12): negative IPO-like and PDO-like circulation anomalies are detected in one simulation only. At these timescales, rainfall variability is primarily driven by enhanced activity in the subtropical Highs in the Southern Hemisphere, in approximate agreement with observations (Fig. 12).

MPI models perform well at the interannual and QDV timescales (Fig. 10). In MPI-ESM-LR, the westward shift and intensification of the Walker circulation associated with wet conditions in SA is realistic in all simulations at both timescales (Fig. 12). However, at the interannual timescale, the Gill-Matsuno response over the Indian Ocean in response to diabatic heating anomalies over the western Pacific is not reproduced (Fig. 12): this may reflect Indian Ocean SSTs, which are too cold, but further work is needed here. In MPI models, interannual rainfall

651 variability is then not directly linked to the Pacific Ocean, but to regional changes in the South

652 Atlantic and South Indian Highs (Fig. 11), which could be related to the SAM (Ciasto et al.

653 2011). At the QDV timescale, the Gill-Matsuno response is simulated too far west, and is

654 reversed compared to observation (Figs. 11-12), consistently with too cold SSTs over the

655 Maritime continent (Fig. 8). Interestingly, strong anomalous Gill-Matsuno responses (*e.g.*

656 r1i1p1) lead to overestimate SA rainfall QDV, while weak anomalous Gill-Matsuno response

657 (e.g. r3i1p1) lead to underestimations (Figs. 2, 12).

658

659 Taken together, the results of this section show that, while atmospheric bridges between the

660 Pacific Ocean and SA are crucial at all timescales in the observations, only few CMIP5 models

661 are able to reproduce it. In some models, simulated rainfall in SA is likely to be associated with

662 error compensations and strongly biased large-scale mechanisms even in cases where regional-

663 scale properties are realistically reproduced.

664

7. Discussion & Conclusion

666 This study is a first assessment of CMIP5 model performances in simulating SA rainfall

667 variability and its teleconnections with large-scale modes of variability at different timescales.

668 Historical runs from 28 models, and their associated piControl run ensembles, have been used

669 to document the weight of sampling errors and internal climate variability.

670

671 Firstly, we examined the ability of CMIP5 models to simulate realistic summer SA rainfall

672 variability, which exhibits three major timescales in observation (Dieppois et al. 2016):

673 interannual (2–8 years), QDV (8–13 years) and IDV (15–28 years). CMIP5 models produce

674 their own variability, but tend to perform better in simulating interannual timescales of SRI

675 variability. Indeed, most models strongly underestimate rainfall variability at the QDV and IDV

676   scales, suggesting a limited view of prolonged drought and hydro-meteorological risks in

677   CMIP5 models over SA. Highest skills in simulating SRI QDV and IDV are however obtained

678   with best performing models at the interannual timescale, suggesting cross-linkages in model

679   biases between timescales which could be used to improve the future generations of climate

680   models. These limitations in simulating SRI variability are partly due to spatial shifts in the

681   core regions of rainfall variability.

682

683   Secondly, CMIP5 model performances in portraying global SST variability at the three different

684   timescales was assessed, as well as their teleconnections with SA rainfall. In observation, wet

685   rainfall conditions over SA are associated with cold SSTs in the Pacific, mostly driven by

686   ENSO, the IPO and the PDO, which interact with regional climate anomalies in the South

687   Atlantic and South Indian Ocean (Dieppois et al. 2016; Pohl et al. 2018). Most models

688   reproduce La Niña effects on rainfall at the interannual timescale, in spite of biases in the

689   representation of ENSO (*e.g.* AchutaRao and Sperber 2006; Guilyardi et al. 2009). At the QDV

690   timescale, some models succeed in reproducing the association between the IPO and SA

691   rainfall, but IPO variability is systematically too weak, and extends too far west (Henley et al.

692   2017). Similarly at the IDV timescale, very few models reproduce negative PDO anomalies.

693   Yet, good performances in simulating the large-scale teleconnections with the Pacific do not

694   systematically lead to good representation of SA rainfall variability. This is because Pacific

695   modes of variability are most of the time associated with biased regional climate anomalies in

696   the adjacent oceans to SA, which, according to Hoell et al. (2017), can substantially modulate

697   their impact on the continent.

698

699   Some CMIP5 simulations do not reproduce, or even significantly reverse, the average link

700   between SA rainfall and Pacific SST variability at the interannual and QDV scales. Even though

this result suggests strong model limitations, such an unlikely configuration has already been

observed in rare occasions: during the exceptionally strong El Niño event of 1997/98, for

instance (Lyon and Mason 2007). In IPSL models and ACCESS1-3, such an unlikely

association between SA rainfall and El Niño anomalies could be due to errors in modelling the

seasonality of ENSO (Fig. A7). CMIP5 model limitations in fully-capturing the relationship

between the SAM and ENSO, and their combined impact on summer-rainfall in the Southern

Hemisphere, could also be crucial, as suggested in Lim et al. (2016). However, such errors do

not systematically impact the realism of simulated rainfall variability here. This is because of

error compensations, mostly resulting from substantial overestimation of SST variability in the

South Atlantic and South Indian Oceans, leading to appropriate simulations of SA rainfall

variability.

All together these results also highlight the potential importance of the South Atlantic and

Indian Ocean SSTs for SA rainfall, as suggested in earlier studies (Nicholson and Kim 1997;

Reason 1998 2001; Reason et al. 1999; Hoell et al. 2015, 2017, 2018; Morioka et al. 2015), and

in modulating the skills of CMIP5 models. They also emphasize the need for process-oriented

studies rather than merely descriptive work for model evaluation, since statistically coherent

regional variability can be obtained from biased large-scale teleconnections and mechanisms.

This issue is of crucial importance for operational seamless predictions and future climate

projections (*e.g.* Mason 1998; Landman and Beraki 2012; Beraki et al. 2014; Landman et al

2017).

Thirdly, the respective contributions of model errors and internal climate variability to overall

uncertainties have been disentangled using probabilistic multi-scale clustering. This new

methodology is strongly recommended for future model evaluation studies at regional and

decadal scales to assess and narrow the impact of internal climate variability. At the global scale, model uncertainties in SST variability are primarily driven by differences from one model to another. At the regional scale, *i.e.* SA rainfall variability and associated teleconnections, model uncertainties are also mainly related to differences in model physics at the interannual timescale. At the QDV and IDV scales, however, individual simulations from the same models, or comparable models, progressively differentiate, which, consistently with Keenlyside et al. (2008), suggests larger contributions of internal climate variability. Uncertainties related to the sample size (length and number of simulations) have also been assessed using piControl runs, and suggest that better performances could be obtained, at least on interannual and QDV scales, in many CMIP5 models using longer-runs. Better impact-assessment of future prolonged drought and hydro-meteorological risks over SA could therefore be obtained using large-ensemble (*e.g.* Kay et al. 2015).

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Figures and Captions

Table 1 Summarized information on observation data and CMIP5 models used in the study.

Table 2 Different components of CMIP5 CGCMs used in the study. Shades of orange, blue,

green and grey indicate shared components between CGCMs from different institutions.

Fig. 1 Summer (NDJF) differences between simulated and observed SA rainfall fields. **a**

Multimodel mean of 95 historical runs from 28 CMIP5 models of summer-rainfall average

minus the CRU TS 3.24.01 observations, compared to the NDJF rainfall climatology (*black*

dashed contours), between 1901 and 2005. Statistical significance of differences in mean (*white*

colours) has been estimated using a Student *t*-test at $p = 0.05$. **b** CMIP5 Multimodel agreement

in the difference in summer-rainfall average compared with observation **c** Spatial distribution

of the summer-rainfall region in the CMIP5 models (*coloured contours refer to each individual*

model; cf. Table 1) and in the CRU TS 3.24.01 observations (*grey shaded*). **d** Multimodel

agreement in the location of the summer-rainfall region in the CMIP5 models compared to

observation (*grey contour*). The summer-rainfall region, which is used to calculate the SRI, has

been defined as the area in which the wettest month of the year occur between November and

February on average between 1901 (1850/60) and 2005 in the observations (CMIP5 models).

Fig. 2 Timescales of variability in the simulated and observed SRI. **a** Comparison between FFT spectra from observation (CRU TS 3.24.01: 1901–2005) and 95 historical runs from 28 CMIP5 models (1850/60–2005). *Bold contour lines* show the probability limits at $p = 0.05$ based on 1000 Monte Carlo simulations of the red noise background spectrum. White crosses indicate area where FFT power spectral density could have been influenced by the sampling period. **b** Centred Ratio of standard deviation (1-rSD), here expressed in percentage, between simulations and observation according to the three dominant time-scales of variability. *Bold contour lines* indicates CMIP5 models simulating significantly equal SRI variance than observations at $p = 0.05$ according to the Fisher's *F*-test. Summary of the mean biases per timescales is provided on the bottom left corner (*all model simulations: black; model simulation overestimating [underestimating] interannual variability: blue [red]*).

Fig. 3 Summary of observed summer (NDJF) SA rainfall variability and its teleconnection with global SSTs at three different timescales. **a** Spatial patterns of rainfall standard deviations in observations (CRU TS 3.24.01). **b** Observed spatial patterns of global SST standard deviations (ERSSTv.4). *Bold red contour lines* delineates area where observed interannual to IDV variance are significantly greater than the red noise background spectrum at $p = 0.05$ based on 1000 Monte Carlo simulations. **c** Observed global SST composite anomalies (ERSSTv.4) during enhanced SRI fluctuations (± 1 SD: wet years minus dry years) at the three different timescales. Statistical significance (*contours*) has been estimated by testing the difference in mean between SST anomalies during periods of rainfall variability greater and lower than 1 SD, through a modified *t*-test accounting for pseudoreplication in the series at $p = 0.05$. Displayed composite SST anomalies refer to wet conditions in SA, but are strictly opposite during dry conditions (cf. Fig. A1).

Fig. 4 Evaluation of model performance and their diversity in simulating SA rainfall variance at three different timescales. **a-c** Taylor diagram of summer (NDJF) rainfall variance spatial patterns of 95 historical runs from 28 CMIP5 models (*coloured dot referring to each individual model; cf. Table 1*) and from observations (CRU TS 3.24.01; *grey dot*) at the IDV to interannual timescales. The diagram is a function of the root mean square (RMS, *green dashed circles–x-axis*), the correlation coefficient (*black dashed lines–y-axis*) and the SD (*blue dashed compared to solid circles–x-axis*). Since the values are normalized the reference (observation values) has a SD of 1. **d** Cluster diversity as determined using AHC, and in assessing significance of each cluster using multiscale bootstrapping. Colours indicate different clusters, and non-significantly clustered simulations are in white. Simulated rainfall fields have been remapped on a regular $0.5° \times 0.5°$ resolution grid to be compared to observation.

Fig. 5 Summer-rainfall variance over SA at three different timescales in CMIP5 models. **a-c** Spatial patterns of rainfall standard deviations in six selected clusters from full CMIP5 multimodel ensemble at the interannual to IDV timescales. *Dark red to dark blue contours lines on the bottom panels* delineates areas where IDV to interannual variance are significantly different than in observations at $p = 0.05$ according to the Fisher's F-test. The selected six clusters are ranked according to their variance (var), here expressed as the percentage of simulations in each cluster. Spatial correlations (cor[obs.]) between simulated and observed patterns are displayed for information purpose. *Asterisks* indicate significant Pearson's correlations at $p = 0.05$ between the cluster and the observed pattern. Note that QDV and IDV standard deviations have been multiplied by 2 for illustrative purpose. Simulated rainfall fields have been remapped on a regular $0.5° \times 0.5°$ resolution grid to be compared to observation.

Fig. 6 Evaluation of model performance and their diversity in simulating NDJF SST variance and global SST composite anomalies at three different timescales. **a** Taylor diagram of NDJF SST variance spatial patterns of 95 historical runs from 28 CMIP5 models (*coloured dot referring to each individual model; cf. Table 1*) and from observations (ERSSTv.4; *grey dot*) at the IDV to interannual timescales. **b** as for **a** but for SST composite anomalies during enhanced SRI (± 1 SD: wet years minus dry years). **c** Cluster diversity for global SST variance and composite anomalies as determined using AHC, and in assessing significance of each cluster using multiscale bootstrapping. Colours indicate different clusters, and non-significantly clustered simulations are in white.

Fig. 7 NDJF global SST variance at three different timescales in CMIP5 models. **a-c** Spatial patterns of global SST standard deviations in six selected clusters from full CMIP5 multimodel ensemble at the interannual to IDV timescales. *Dark red to dark blue contours lines* delineates areas where SST variance are significantly different than in observations at $p = 0.05$ according to the Fisher's F-test. The selected six clusters are ranked according to their variance (var), here expressed as the percentage of simulations in each cluster. Spatial correlations (cor[obs.]) between simulated and observed patterns are displayed for information purpose. *Asterisks* indicate significant Pearson's correlations at $p = 0.05$ between clusters and the observed pattern.

Fig. 8 as **Fig. 7** but for global SST composite anomalies in the CMIP5 models. *Black and grey contours* indicate that statistical significance of composite anomalies was reached in 50% of the model defining the cluster. Composite anomalies and statistical significances have been estimated as defined in Figure 3. The selected six clusters are ranked according to their variance (var), here expressed as the percentage of simulations in each cluster. Spatial correlations (cor[obs.]) between simulated and observed patterns are displayed for information purpose. *Asterisks* indicate significant Pearson's correlations at $p = 0.05$ between clusters and the observed pattern.

Fig. 9 Comparison of performances in simulating SRI variability and associated SST teleconnections in the different ocean basins. Percentage of CMIP5 simulations associated with contrasted performances in SST variability and associated teleconnections has been quantified. +SST/+SRI refers to simulations with good SRI variability (*i.e.* significantly equal variance according to a Fisher F-test at $p = 0.05$) and good SST teleconnection patterns (*i.e.* Person correlations with observation ≥ 0.5). OppSST indicates simulations with good SRI variability, but opposite SST teleconnection patterns (*i.e.* Person correlation with observation < 0). +SST/-SRI refers to simulations with poor SRI variability (*i.e.* not significantly equal variance according to a Fisher F-test at $p = 0.05$), but with good SST teleconnection patterns. -SST/+SRI denotes simulations with good SRI variability, but with poor SST teleconnection patterns (*i.e.* Person correlations with observation < 0.5).

Fig. 10 Sample size uncertainties and model capabilities at the three different timescales. **a** Capability to simulate observed SRI variance (significant equal variance according to a Fisher F-test at $p = 0.05$) in all historical runs from the 28 CMIP5 models (*top*), and in their associated pi-Control runs (*bottom*). **b** Capability to simulate similar teleconnections (*i.e*. Pearson correlations ≥ 0.5) in all historical runs from the 28 CMIP5 models (*top*), and in their associated pi-Control runs (*bottom*). Grey dot sizes refer to the number of sampled used to estimate the model capabilities, and should be used as an indicator of robustness.d

Fig. 11 Atmospheric bridges between the Pacific Ocean and SA in 20CR.v2c. NDJF velocity potential (*φ; shaded*) and stream function (*ψ; contours*) composite anomalies between 850 and 600 hPa *(left)*, and between 400 and 150 hPa *(right)*, during enhanced SRI fluctuations (±1 SD: wet years minus dry years) at the three different timescales. Composite anomalies and statistical significances have been estimated as defined in Figure 3. Only significant velocity potential and stream function anomalies at $p = 0.05$ are displayed. Note: IDV anomalies are multiplied by 1.5 to be clearly displayed.

Fig. 12 Atmospheric bridges between the Pacific Ocean and SA in selected CMIP5 models. **a-c** Simulated NDJF velocity potential (*φ; shaded*) and stream function (*ψ; contours*) composite anomalies between 850 and 600 hPa during enhanced SRI fluctuations (±1 SD: wet years minus dry years) at the three different timescales. Composite anomalies and statistical significances have been estimated as defined in Figure 3. Only significant velocity potential and stream function anomalies at $p = 0.05$ are displayed. Note: IDV anomalies are multiplied by 1.5 to be clearly displayed.

1167 **Fig. A1** Comparison between SST composite anomalies associated with wet and dry conditions

1168 in SA. **a-c** Scatterplot of observed SST composite anomalies during wet (positive SRI

1169 anomalies = +1 SD) and dry (negative SRI anomalies = -1 SD) conditions at the interannual

1170 (*left*), QDV (*middle*) and IDV (*right*) timescales. **d-f** as **a-c** but for 95 historical runs from 28

1171 CMIP5 models. Scatter plots are smoothed and coloured (*low to high probability = blue, yellow*

1172 *to red*) using a 2D kernel density estimate. Red and black lines refer to the regression lines

1173 between wet and dry SST composite anomalies, and associated correlation coefficients are

1174 provided in the lower left corner on each panel.

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1176 **Fig. A2** Step-by-step process of the multi-scale bootstrap clustering. Step-0: 10 simulated

1177 patterns of global SST variability are submitted to the clustering approach. Step-1: simulated

1178 patterns are resampled ni times, using rj scales (referring to different sizes of the spatial

1179 domain). Step-2: ni × rj Agglomerative hierarchical clustering are produced, using Ward's

1180 agglomerative criteria applied to Euclidian distances. Step-3: the probability of each

1181 simulations to be clustered with the others (red values) is estimated. Here, only two clusters are

1182 significantly robust at $p \geq 0.90$.

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1184 **Fig. A3** Percentage of occurrence of significant signals within the interannual, QDV and IDV

1185 timescales of SRI variability in all (95) model simulations, in all (28) models and all (16)

1186 institutions using the CMIP5 historical experiments. Statistical significance was estimated at

1187 $p=0.05$ based 1000 Monte Carlo simulations of the red noise background spectrum.

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1189 **Fig. A4** Boxplots of the correlations between simulations of the same models (intra-ensembles;

1190 blue), and of different models (inter-models; red), of the CMIP5 historical experiments in

1191 reproducing spatial patterns of SA rainfall variability at the three different timescales.

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Fig. A5 Distributions of model simulations in clustering patterns of SA rainfall variability, global SST variability, and teleconnections at the interannual to interdecadal timescales. The six selected clusters, which are shown in Figures 5, 7 and 8, are in bold.

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Fig. A6 Boxplots of the correlations between simulations of the same models (intra-ensembles; blue), and of different models (inter-models; red), of the CMIP5 historical experiments in reproducing spatial patterns of global SST variability (shaded), and SST composite anomalies associated with SA rainfall variability (not shaded) at the three different timescales.

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Fig. A7 Mean annual cycle of monthly standard deviations of SST anomalies over the Niño3.4 region (*i.e.* 5°S-5°N and 120-170°W) in the CMIP5 models (*coloured contours refer to each individual model; cf. Table 1*) and in the CRU TS 3.24.01 observations (*grey shaded*). SST anomalies are here calculated by subtracting the monthly climatology according to the definition of the Niño3.4 index (Trenberth 1997). To reduce the influence of the global trends, SST anomalies are detrended using a locally weighted linear regressions, with span equal to the length of the data.

Figure 1

a) CMIP5-MM NDJF rainfall: Mean Bias

b) CMIP5-MM agreement: Mean bias

c) CMIP5-MM agreement: Summer-rain Region

Figure 2

a) FFT spectra CMIP5 Models

b) Ratio of standard deviation (rSD) between CMIP5 Models and obs.

Figure 3

a) Rainfall variability

b) SST variability

c) SRI-SST anomalies

Standard Deviation *(mm.month⁻¹)*: 3 — 24

Standard Deviation *(C)*: 0.05 — 0.25

SST composite anomalies *(C)*: -0.35 — 0.35

Figure 4

Figure 5

a) CMIP5 Int. — **b) CMIP5 QDV** — **C) CMIP5 IDV**

Column a) CMIP5 Int.:
- #Cluster1 — Var=18.9%, Cor[obs]=0.87*
- #Cluster13 — Var=13.7%, Cor[obs]=0.86*
- #Cluster6 — Var=9.5%, Cor[obs]=0.82*
- #Cluster10 — Var=7.4%, Cor[obs]=0.71*
- #Cluster7 — Var=6.3%, Cor[obs]=0.90*
- #Cluster2 — Var=5.3%, Cor[obs]=0.85*

Column b) CMIP5 QDV:
- #Cluster2 — Var=9.5%, Cor[obs]=0.66*
- #Cluster1 — Var=8.4%, Cor[obs]=0.67*
- #Cluster25 — Var=5.3%, Cor[obs]=0.57*
- #Cluster24 — Var=4.2%, Cor[obs]=0.65*
- #Cluster5 — Var=3.2%, Cor[obs]=0.71*
- #Cluster21 — Var=3.2%, Cor[obs]=0.68*

Column C) CMIP5 IDV:
- #Cluster7 — Var=9.5%, Cor[obs]=0.74*
- #Cluster1 — Var=6.3%, Cor[obs]=0.86*
- #Cluster6 — Var=4.2%, Cor[obs]=0.78*
- #Cluster14 — Var=4.2%, Cor[obs]=0.23*
- #Cluster9 — Var=3.2%, Cor[obs]=0.75*
- #Cluster12 — Var=3.2%, Cor[obs]=0.77*

Standard Deviation (mm): 3 to 24

CMIP5 minus Obs (mm): -16 -12 -8 -4 4 8 12 16

Figure 6

a) Taylor Diag. SST variability

b) Taylor Diag. SST anomalies

c) Cluster diversity

Figure 7

a) CMIP5 Int.

#cluster3
var=11.6%
cor[obs]=0.76*

#cluster1
var=10.5%
cor[obs]=0.59*

#cluster12
var=10.5%
cor[obs]=0.68*

#cluster6
var=7.4%
cor[obs]=0.64*

#cluster13
var=7.4%
cor[obs]=0.61*

#cluster7
var=6.3%
cor[obs]=0.58*

b) CMIP5 QDV

#cluster2
var=11.6%
cor[obs]=0.53*

#cluster8
var=11.6%
cor[obs]=0.74*

#cluster1
var=10.5%
cor[obs]=0.53*

#cluster9
var=7.4%
cor[obs]=0.54*

#cluster4
var=6.3%
cor[obs]=0.38*

#cluster12
var=6.3%
cor[obs]=0.56*

c) CMIP5 IDV

#cluster10
var=13.7%
cor[obs]=0.58*

#cluster11
var=11.6%
cor[obs]=0.54*

#cluster1
var=10.5%
cor[obs]=0.56*

#cluster7
var=10.5%
cor[obs]=0.45*

#cluster3
var=7.4%
cor[obs]=0.60*

#cluster15
var=6.3%
cor[obs]=0.46*

Standard Dev. *(c)*
0.05
0.25

CMIP5 minus Obs *(c)*
-0.2
-0.1
0.1
0.2

Figure 8

a) CMIP5 Int. Ano.   b) CMIP5 QDV Ano.   c) CMIP5 IDV Ano.

#cluster9   #cluster24   #cluster4
var=10.5%   var=8.4%   var=4.2%
cor[obs.]=0.45*   cor[obs.]=0.74*   cor[obs.]=0.43*

#cluster10   #cluster12   #cluster7
var=7.4%   var=6.3%   var=4.2%
cor[obs.]=0.40*   cor[obs.]=0.01*   cor[obs.]=0.18*

#cluster7   #cluster21   #cluster14
var=6.3%   var=4.2%   var=3.2%
cor[obs.]=-0.18*   cor[obs.]=0.64*   cor[obs.]=0.33*

#cluster6   #cluster1   #cluster17
var=5.3%   var=3.2%   var=3.2%
cor[obs.]=0.68*   cor[obs.]=0.38*   cor[obs.]=0.07*

#cluster4   #cluster9   #cluster1
var=4.2%   var=3.2%   var=2.1%
cor[obs.]=0.60*   cor[obs.]=0.20*   cor[obs.]=0.55*

#cluster8   #cluster11   #cluster2
var=3.2%   var=3.2%   var=2.1%
cor[obs.]=-0.68*   cor[obs.]=-0.13*   cor[obs.]=0.56*

SST Composite Anomalies (c)

-0.35

0.35

Figure 9

Interannual

	+SST/+SRI	OppSST	+SST/-SRI	-SST/+SRI
N Pac	28.4%	12.6%	30.5%	23.2%
T Pac	28.4%	12.6%	30.5%	23.2%
S Ind	14.7%	2.1%	23.2%	36.8%
T Ind	18.9%	8.4%	16.8%	32.6%
S Atl	11.6%	5.3%	24.2%	40%
Global	20%	3.2%	24.2%	31.6%

QDV

	+SST/+SRI	OppSST	+SST/-SRI	-SST/+SRI
N Pac	9.5%	7.4%	34.7%	22.1%
T Pac	9.5%	7.4%	34.7%	22.1%
S Ind	8.4%	1.1%	26.3%	23.2%
T Ind	5.3%	1.1%	11.6%	26.3%
S Atl	5.3%	1.1%	23.2%	26.3%
Global	4.2%	0%	15.8%	27.4%

IDV

	+SST/+SRI	OppSST	+SST/-SRI	-SST/+SRI
N Pac	4.2%	1.1%	21.1%	14.7%
T Pac	4.2%	1.1%	21.1%	10.5%
S Ind	2.1%	0%	16.8%	12.6%
T Ind	2.1%	2.1%	14.7%	12.6%
S Atl	4.2%	3.1%	29.5%	10.5%
Global	0%	0%	1.1%	14.7%

% Model simulations

Figure 10

a) Prob. Obs. SA rainfall variance

b) Prob. Obs. link with Global SST

Figure 11

Lower Troposphere

Upper Troposphere

Interannual

Velocity potential
& Stream function

850-600hPa

Velocity potential
& Stream function

400-150hPa

QDV

Velocity potential
& Stream function

850-600hPa

Velocity potential
& Stream function

400-150hPa

IDV

Velocity potential
& Stream function

850-600hPa

Velocity potential
& Stream function

400-150hPa

Velocity potential anomalies *(m².s⁻¹)*

-18e5   -15e5   -12e5   -6e5   6e5   12e5   15e5   18e5

Stream function anomalies *(m².s⁻¹)*

-15e5   -6e5   6e5   15e5

Figure 12

a) CMIP5: Interannual   **b) CMIP5: QDV**   **c) CMIP5: IDV**

GISS-E2-R-CC — *Least performant*

IPSL-CM5B-LR

GFDL-CM3 (r1i1p1, r5i1p1) — *Most performant*

MPI-ESM-LR (r1i1p1, r3i1p1)

Velocity potential & Stream function

850-600hPa

Velocity potential anomalies ($m^2.s^{-1}$): -18e5, -15e5, -12e5, -6e5, 6e5, 12e5, 15e5, 18e5
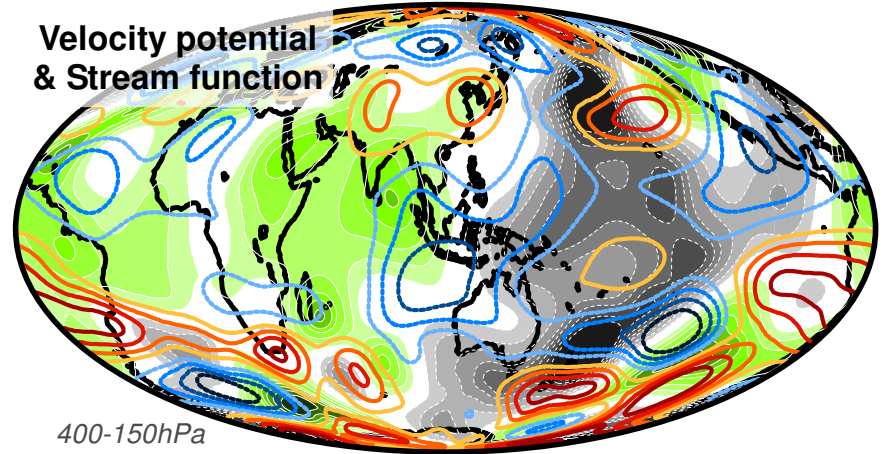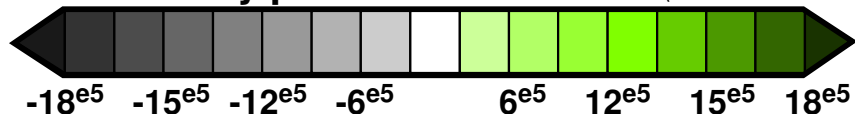
Stream function anomalies ($m^2.s^{-1}$): -15e5, -6e5, 6e5, 15e5
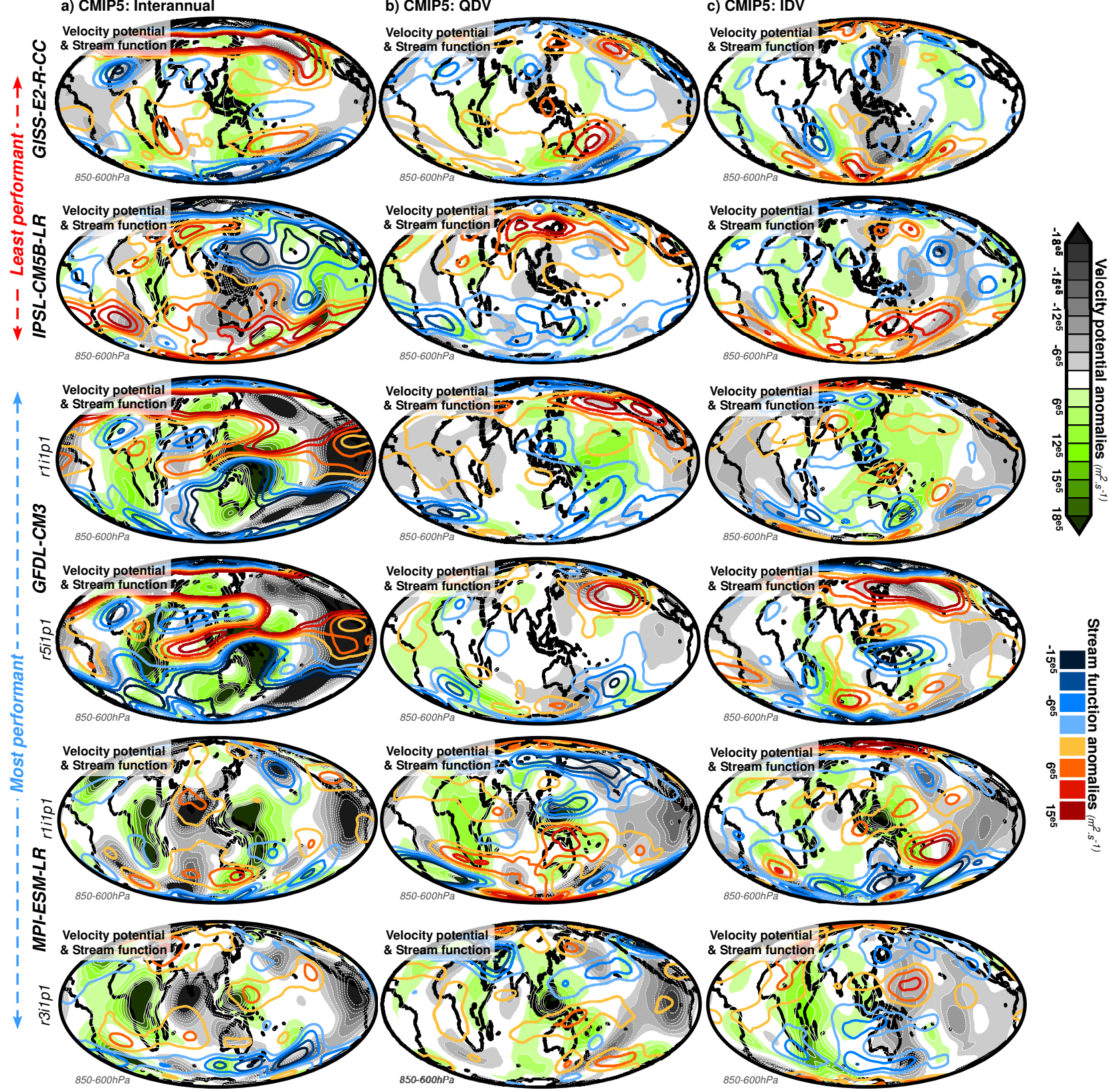
Table 1

	Institution	Name	Member	Variable	Hist. period	piControl length (yr)	Atmos. Grid (lat x lon)	Color ID
Obs.	CRU, UK	CRU TS 3.24.1	○	pr		○	1 x 1	○
	NOAA-NCDC, USA	ERSS.v4	○	sst	1901-2014	○		○
	NOAA-CIRES, USA	20CR.v2c	56	φ, ψ		○	2 x 2	○
CMIP5 Model outputs	BCC, China	bcc-csm1-1	3	pr, sst, φ, ψ	1850-2005	500	2.7906 x 2.8125	
		bcc-csm1-1-m	3			400	1.13 x 1.13	
	CCCma, Canada	CanESM2	5	pr, sst, φ, ψ	1850-2005	996	2.7906 x 2.8125	
	CMCC, Italy	CMCC-CESM	1			277	3.4431 x 3.75	
		CMCC-CM	1	pr, sst, φ, ψ	1850-2005	329	0.7484 x 0.75	
		CMCC-CMS	1			500	3.7111 x 3.75	
	CNRM, France	CNRM-CM5	10	pr, sst, φ, ψ	1850-2005	850	1.4008 x 1.40625	
	CSIRO-BOM, Australia	ACCESS1-0	1	pr, sst, φ, ψ	1850-2005	500	1.25 x 1.875	
		ACCESS1-3	3		1850-2005	500		
	CSIRO-QCCCE, Australia	CSIRO-Mk3-6-0	10	pr, sst, φ, ψ	1850-2005	500	1.8653 x 1.875	
	INM, Russia	inmcm4	1	pr, sst, φ, ψ	1850-2005	500	1.5 x 2	
	IPSL, France	IPSL-CM5A-LR	6			1000	1.8947 x 3.75	
		IPSL-CM5A-MR	3	pr, sst, φ, ψ	1850-2005	300	1.2676 x 2.5	
		IPSL-CM5B-LR	1			300	1.8947 x 3.75	
	MIROC, Japan	MIROC5	5	pr, sst, φ, ψ	1850-2005	670	1.4008 x 140625	
	MOHC, UK	HadGEM2-CC	1	pr, sst, φ, ψ	1860-2005	240	1.25 x 1.875	
		HadGEM2-ES	4			577		
	MPI-M, Germany	MPI-ESM-LR	3	pr, sst, φ, ψ	1850-2005	1000	1.8653 x 1.875	
		MPI-ESM-MR	3			1000		
	NASA-GISS, USA	GISS-E2-H	6			780		
		GISS-E2-R	6	pr, sst, φ, ψ	1850-2005	850	2 x 2.5	
		GISS-E2-R-CC	1			251		
	NCAR, USA	CCSM4	6	pr, sst, φ, ψ	1850-2005	1051	1.25 x 0.94	
	NCC, Norway	NorESM1-M	3	pr, sst, φ, ψ	1850-2005	501	1.8947 x 2.5	
		NorESM1-ME	1			252		
	NOAA-GFDL, USA	GFDL-CM3	5	pr, sst, φ, ψ	1860-2005	500	2 x 2.5	
		GFDL-ESM2M	1		1861-2005	500	2.0225 x 2.5	
	NSF-DOE-NCAR, USA	CESM1-BCG	1	pr, sst, φ, ψ	1850-2005	500	1.25 x 0.94	

Table 2

Institution	Name	Atmospheric Comp.	Ocean Comp.	Land Comp.	Sea-Ice Comp.
BCC, *China*	bcc-csm1-1	BCC-AGCM2-1	MOM4-1	BCC-AVIM1-0	SIS
	bcc-csm1-1-m	BCC-AGCM2-1			
CCCma, *Canada*	CanESM2	CanCM4	CanOM4	CTEM	o
CMCC, *Italy*	CMCC-CESM	ECHAM5	OPA8-2	SILVA	LIM
	CMCC-CM				
	CMCC-CMS				
CNRM, *France*	CNRM-CM5	ARPEGE	NEMO3-2	ISBA	GELATO
CSIRO-BOM, *Australia*	ACCESS1-0	HadCM3	MOM4-1	MOSES2	CICE
	ACCESS1-3	MO GA1-0			
CSIRO-QCCCE, *Australia*	CSIRO-Mk3-6-0	CSIRO-Mk3	MOM2-2	o	~CICE
INM, *Russia*	inmcm4	INMAM	INMOM	o	o
IPSL, *France*	IPSL-CM5A-LR	LMDZ5A	NEMO3-2	ORCHIDEE	LIM
	IPSL-CM5A-MR				
	IPSL-CM5B-LR	LMDZ5B			
MIROC, *Japan*	MIROC5	FRCGCM	COCO	MATSIRO	COCO
MOHC, *UK*	HadGEM2-CC	HadCM3	HadGOM1	MOSES2	CICE
	HadGEM2-ES				
MPI-M, *Germany*	MPI-ESM-LR	ECHAM6	MPI-OM	JSBACH	o
	MPI-ESM-MR				
NASA-GISS, *USA*	GISS-E2-H	ModelE2	Russel	o	o
	GISS-E2-R		HYCOM		
	GISS-E2-R-CC				
NCAR, *USA*	CCSM4	CAM4	POP	CLM4	CICE
NCC, *Norway*	NorESM1-M	CAM4	MICOM	CLM4	CICE
	NorESM1-ME				
NOAA-GFDL, *USA*	GFDL-CM3	AM3	MOM4-1	LM3	SIS
	GFDL-ESM2M	AM2			
NSF-DOE-NCAR, *USA*	CESM1-BCG	CAM4	POP2	CLM4	CICE

CMIPS Model outputs